Package 'gmvarkit'

October 5, 2020

Title Estimate Gaussian Mixture Vector Autoregressive Model

Version 1.2.2

Description
Unconstrained and constrained maximum likelihood estimation of structural and reduced form Gaussian mixture vector autoregressive (GMVAR) model, quantile residual tests, graphical diagnostics,
simulations, forecasting, and estimation of generalized impulse response function.
Leena Kalliovirta, Mika Meitz, Pentti Saikkonen (2016) <doi:10.1016/j.jeconom.2016.02.012>, Savi Virolainen (2020) <arXiv:2007.04713>.

Depends R (>= 4.0.0)

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Encoding UTF-8

LazyData true

RoxygenNote 7.1.1

Imports Brobdingnag (>= 1.2-6), mvnfast (>= 0.2.5), parallel (>= 4.0.0), stats (>= 4.0.0), pbapply (>= 1.4-2), graphics (>= 4.0.0), grDevices (>= 4.0.0)

Suggests testthat, knitr, rmarkdown

VignetteBuilder knitr

NeedsCompilation no

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Repository CRAN

Date/Publication 2020-10-05 17:10:02 UTC

R topics documented:

`add_data` *Add data to an object of class 'gmvar' defining a GMVAR model*

Description

`add_data` adds or updates data to object of class '`gmvar`' that defines a GMVAR model. Also calculates mixing weights and quantile residuals accordingly.

Usage

```
add_data(data, gmvar, calc_cond_moments = TRUE, calc_std_errors = FALSE)
```

Arguments

data	a matrix or class 'ts' object with d>1 columns. Each column is taken to represent a single time series. NA values are not supported.
gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.
calc_cond_moments	should conditional means and covariance matrices should be calculated? Default is TRUE if the model contains data and FALSE otherwise.
calc_std_errors	should approximate standard errors be calculated?

Value

Returns an object of class 'gmvar' defining the specified GMVAR model with the data added to the model. If the object already contained data, the data will be updated.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

fitGMVAR, GMVAR, iterate_more

Examples

```
# These examples use the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(1,2), d=2 model:
params122 <- c(0.623, -0.129, 0.959, 0.089, -0.006, 1.006, 1.746,
 0.804, 5.804, 3.245, 7.913, 0.952, -0.037, -0.019, 0.943, 6.926,
 3.982, 12.135, 0.789)
mod122 <- GMVAR(p=1, M=2, d=2, params=params122)
mod122

mod122_2 <- add_data(data, mod122)
mod122_2


# GMVAR(2,2), d=2 model with AR-parameters restricted to be
# the same for both regimes:
```

```
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
params222c <- c(1.031, 2.356, 1.786, 3.000, 1.250, 0.060, 0.036,
 1.335, -0.290, -0.083, -0.047, -0.356, 0.934, -0.152, 5.201, 5.883,
 3.560, 9.799, 0.368)
mod222c <- GMVAR(p=2, M=2, d=2, params=params222c, constraints=C_mat)
mod222c

mod222c_2 <- add_data(data, mod222c)
mod222c_2

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(1.03, 2.36, 1.79, 3, 1.25, 0.06, 0.04, 1.34, -0.29,
 -0.08, -0.05, -0.36, 1.2, 0.05, 0.05, 1.3, -0.3, -0.1, -0.05, -0.4,
  0.89, 0.72, -0.37, 2.16, 7.16, 1.3, 0.37)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
mod222s <- GMVAR(p=2, M=2, d=2, params=params222s, structural_pars=list(W=W_222))
mod222s

mod222s_2 <- add_data(data, mod222s)
mod222s_2
```

`all_pos_ints` *Check whether all arguments are positive integers*

Description

`all_pos_ints` checks whether all the elements in a vector are positive integers.

Usage

```
all_pos_ints(x)
```

Arguments

`x`	a vector containing the elements to be tested.

Value

Returns `TRUE` or `FALSE` accordingly.

alt_gmvar *Construct a GMVAR model based on results from an arbitrary estimation round of* fitGMVAR

Description

alt_gmvar constructs a GMVAR model based on results from an arbitrary estimation round of fitGMVAR.

Usage

```
alt_gmvar(
  gmvar,
  which_round = 1,
  which_largest,
  calc_cond_moments = TRUE,
  calc_std_errors = TRUE
)
```

Arguments

gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.
which_round	based on which estimation round should the model be constructed? An integer value in 1,...,ncalls.
which_largest	based on estimation round with which largest log-likelihood should the model be constructed? An integer value in 1,...,ncalls. For example, which_largest=2 would take the second largest log-likelihood and construct the model based on the corresponding estimates. If used, then which_round is ignored.
calc_cond_moments	should conditional means and covariance matrices should be calculated? Default is TRUE if the model contains data and FALSE otherwise.
calc_std_errors	should approximate standard errors be calculated?

Details

It's sometimes useful to examine other estimates than the one with the highest log-likelihood. This function is wrapper around GMVAR that picks the correct estimates from an object returned by fitGMVAR.

Value

Returns an object of class 'gmvar' defining the specified reduced form or structural GMVAR model. Can be used to work with other functions provided in gmvarkit.

Remark that the first autocovariance/correlation matrix in $uncond_moments is for the lag zero, the second one for the lag one, etc.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Kalliovirta L. and Saikkonen P. 2010. Reliable Residuals for Multivariate Nonlinear Time Series Models. *Unpublished Revision of HECER Discussion Paper No. 247*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

`fitGMVAR`, `GMVAR`, `iterate_more`

Examples

```
# These are long running examples and use parallel computing
data(eurusd, package="gmvarkit")
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(1,2) model
fit12 <- fitGMVAR(data, 1, 2, ncalls=2, seeds=7:8)
fit12
fit12_2 <- alt_gmvar(fit12, which_round=1)
fit12_2

# Structural GMVAR(1,2) model identified with sign
# constraints.
W_122 <- matrix(c(1, NA, -1, 1), nrow=2)
fit12s <- fitGMVAR(data, p=1, M=2, structural_pars=list(W=W_122),
  ncalls=2, seeds=1:2)
fit12s
fit12s_2 <- alt_gmvar(fit12s, which_round=2)
fit12s_2
```

`calc_gradient` *Calculate gradient or Hessian matrix*

Description

`calc_gradient` or `calc_hessian` calculates the gradient or Hessian matrix of the given function at the given point using central difference numerical approximation. `get_gradient` or `get_hessian` calculates the gradient or Hessian matrix of the log-likelihood function at the parameter estimates of a class `'gmvar'` object. `get_soc` returns eigenvalues of the Hessian matrix, and `get_foc` is the same as `get_gradient` but named conveniently.

Usage

```
calc_gradient(x, fn, h = 6e-06, ...)

calc_hessian(x, fn, h = 6e-06, ...)

get_gradient(gmvar, h = 6e-06)

get_hessian(gmvar, h = 6e-06)

get_soc(gmvar, h = 6e-06)

get_foc(gmvar, h = 6e-06)
```

Arguments

x	a numeric vector specifying the point where the gradient or Hessian should be calculated.
fn	a function that takes in argument x as the **first** argument.
h	difference used to approximate the derivatives.
...	other arguments passed to fn
gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.

Details

In particular, the functions get_foc and get_soc can be used to check whether the found estimates denote a (local) maximum point, a saddle point, or something else. Note that profile log-likelihood functions can be conveniently plotted with the function profile_logliks.

Value

Gradient functions return numerical approximation of the gradient and Hessian functions return numerical approximation of the Hessian. get_soc returns eigenvalues of the Hessian matrix.

Warning

No argument checks!

See Also

profile_logliks

Examples

```
# Simple function
foo <- function(x) x^2 + x
calc_gradient(x=1, fn=foo)
calc_gradient(x=-0.5, fn=foo)
```

```
# More complicated function
foo <- function(x, a, b) a*x[1]^2 - b*x[2]^2
calc_gradient(x=c(1, 2), fn=foo, a=0.3, b=0.1)

# These examples below use the data 'eurusd' which comes
# with the package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)


# GMVAR(1,2), d=2 model:
params122 <- c(0.623, -0.129, 0.959, 0.089, -0.006, 1.006, 1.746,
  0.804, 5.804, 3.245, 7.913, 0.952, -0.037, -0.019, 0.943, 6.926,
  3.982, 12.135, 0.789)
mod122 <- GMVAR(data, p=1, M=2, params=params122)
get_gradient(mod122)
get_hessian(mod122)
get_soc(mod122)
```

`change_parametrization` *Change parametrization of a parameter vector*

Description

`change_parametrization` changes the parametrization of the given parameter vector to `change_to`.

Usage

```
change_parametrization(
  p,
  M,
  d,
  params,
  constraints = NULL,
  structural_pars = NULL,
  change_to = c("intercept", "mean")
)
```

Arguments

`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`d`	the number of time series in the system.
`params`	a real valued vector specifying the parameter values. **For unconstrained models:** Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M)$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by ***Kalliovirta, Meitz and Saikkonen (2016)*** introducing the GMVAR model.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p}) (pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

`change_to` either "intercept" or "mean" specifying to which parametrization it should be switched to. If set to `"intercept"`, it's assumed that `params` is mean-parametrized, and if set to `"mean"` it's assumed that `params` is intercept-parametrized.

Value

Returns parameter vector described in `params`, but with parametrization changed from intercept to mean (when `change_to==mean`) or from mean to intercept (when `change_to==intercept`).

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`change_regime` *Change regime parameters* $\upsilon\_m = (\phi\_m, 0, \phi\_m, \sigma\_m)$ *of the given parameter vector*

Description

`change_regime` changes the regime parameters (excluding mixing weights parameter) of the pointed regime to the new given parameters.

Usage

```
change_regime(p, M, d, params, m, regime_pars, structural_pars = NULL)
```

Arguments

`p` a positive integer specifying the autoregressive order of the model.

`M` a positive integer specifying the number of mixture components.

`d` number of time series in the system, i.e. the dimension.

`params` a real valued vector specifying the parameter values.

For unconstrained models: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M)$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`m` which component?

`regime_pars` **For reduced form models:** a size $((pd^2 + d + d(d+1)/2)x1)$ vector $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$.

For structural models: a length $pd^2 + d$ vector $(\phi_{m,0}, \phi_m)$.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Details

Does not currently support models with AR or lambda parameter constraints.

Value

Returns parameter vector with `m`:th regime changed to `regime_pars`.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`check_constraints` *Check the constraint matrix has the correct form*

Description

`check_constraints` checks that the constraints are correctly set.

Usage

```
check_constraints(p, M, d, constraints = NULL, structural_pars = NULL)
```

Arguments

`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`d`	the number of time series in the system.
`constraints`	a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Details

If `is.null(constraints)`, then this function doesn't do anything.

Value

Checks the constraint matrix **C** and throws an error if something is wrong.

`check_data` *Check the data is in the correct form*

Description

`check_data` checks the data.

Usage

```
check_data(data, p)
```

Arguments

`data`	a matrix or class `'ts'` object with `d>1` columns. Each column is taken to represent a single time series. `NA` values are not supported.
`p`	a positive integer specifying the autoregressive order of the model.

Value

Checks the data and tries to correct it. Throws an error if something is wrong and returns the corrected data otherwise.

check_gmvar *Checks whether the given object has class attribute 'gmvar'*

Description

check_gmvar checks that the object has class attribute 'gmvar'.

Usage

```
check_gmvar(object, object_name)
```

Arguments

object	S3 object to be tested
object_name	what is the name of the object that should of class 'gmvar'?

Value

Throws an error if the object doesn't have the class attribute 'gmvar'.

check_null_data *Checks whether the given object contains data*

Description

check_null_data checks that the gmvar object has data.

Usage

```
check_null_data(gmvar)
```

Arguments

gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.

Value

Throws an error if is.null(gmvar$data).

check_parameters *Check that the given parameter vector satisfies the model assumptions*

Description

check_parameters checks whether the given parameter vector satisfies the model assumptions. Does NOT consider the identifiability condition!

Usage

```
check_parameters(p, M, d, params, constraints = NULL, structural_pars = NULL)
```

Arguments

p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
d	the number of time series in the system.
params	a real valued vector specifying the parameter values.

For unconstrained models: Should be size $((M(pd^2+d+d(d+1)/2+1)-1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace λ_2, ...,λ_M with γ $(rx1)$ that satisfies (λ_2, ..., λ_M) $= C_\lambda\gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If parametrization=="mean", just replace each $\phi_{m,0}$ with regimewise mean μ_m.

$vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

Throws an informative error if there is something wrong with the parameter vector.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

Examples

```
## Not run:
# These examples will cause an informative error

# GMVAR(1, 1), d=2 model:
params112 <- c(1.07, 127.71, 0.99, 0.00, -0.01, 1.00, 4.05,
  2.22, 8.87)
check_parameters(p=1, M=1, d=2, params=params11)
```

```
# GMVAR(2, 2), d=2 model:
params222 <- c(1.39, -0.77, 1.31, 0.14, 0.09, 1.29, -0.39,
 -0.07, -0.11, -0.28, 0.92, -0.03, 4.84, 1.01, 5.93, 1.25,
  0.08, -0.04, 1.27, -0.27, -0.07, 0.03, -0.31, 5.85, 10.57,
  9.84, 0.74)
check_parameters(p=2, M=2, d=2, params=params222)

# GMVAR(2, 2), d=2 model with AR-parameters restricted to be
# the same for both regimes:
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
params222c <- c(1.03, 2.36, 1.79, 3.00, 1.25, 0.06,0.04,
 1.34, -0.29, -0.08, -0.05, -0.36, 0.93, -0.15, 5.20,
 5.88, 3.56, 9.80, 1.37)
check_parameters(p=2, M=2, d=2, params=params222c, constraints=C_mat)

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(1.03, 2.36, 1.79, 3, 1.25, 0.06, 0.04, 1.34, -0.29,
 -0.08, -0.05, -0.36, 1.2, 0.05, 0.05, 1.3, -0.3, -0.1, -0.05, -0.4,
  0.89, 0.72, -0.37, 2.16, 7.16, 1.3, 0.37)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
check_parameters(p=2, M=2, d=2, params=params222s,
 structural_pars=list(W=W_222))

## End(Not run)
```

---

check_pMd *Check that p, M, and d are correctly set*

Description

check_pMd checks the arguments p, M, and d.

Usage

```
check_pMd(p, M, d)
```

Arguments

p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
d	the number of time series in the system.

Value

Throws an error if something is wrong.

cond_moments *Compute conditional moments of a GMVAR model*

Description

loglikelihood compute conditional regimewise means, conditional means, and conditional covariance matrices of a GMVAR model.

Usage

```
cond_moments(
  data,
  p,
  M,
  params,
  parametrization = c("intercept", "mean"),
  constraints = NULL,
  structural_pars = NULL,
  to_return = c("regime_cmeans", "total_cmeans", "total_ccovs")
)
```

Arguments

data	a matrix or class 'ts' object with d>1 columns. Each column is taken to represent a single time series. NA values are not supported.
p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
params	a real valued vector specifying the parameter values.

For unconstrained models: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d + d(d+1)/2 + 1) + q - 1)x1)$ and have form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`parametrization`

`"mean"` or `"intercept"` determining whether the model is parametrized with regime means μ_m or intercept parameters $\phi_{m,0}$, m=1,...,M.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

`to_return` should the regimewise conditional means, total conditional means, or total conditional covariance matrices be returned?

Details

The first p values are used as the initial values, and by conditional we mean conditioning on the past. Formulas for the conditional means and covariance matrices are given in equations (3) and (4) of KMS (2016).

Value

If `to_return=="regime_cmeans"`**:** an `[T-p,d,M]` array containing the regimewise conditional means (the first p values are used as the initial values).

If `to_return=="total_cmeans"`**:** a `[T-p,d]` matrix containing the conditional means of the process (the first p values are used as the initial values).

If `to_return=="total_ccov"`**:** an `[d,d,T-p]` array containing the conditional covariance matrices of the process (the first p values are used as the initial values).

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

Other moment functions: `get_regime_autocovs()`, `get_regime_means()`, `uncond_moments()`

Examples

```
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
params222 <- c(-11.904, 154.684, 1.314, 0.145, 0.094, 1.292, -0.389,
 -0.070, -0.109, -0.281, 0.920, -0.025, 4.839, 11.633, 124.983, 1.248,
  0.077, -0.040, 1.266, -0.272, -0.074, 0.034, -0.313, 5.855, 3.570,
  9.838, 0.740)
cond_moments(data=data, p=2, M=2, params=params222, parametrization="mean",
  to_return="regime_cmeans")
cond_moments(data=data, p=2, M=2, params=params222, parametrization="mean",
  to_return="total_cmeans")
cond_moments(data=data, p=2, M=2, params=params222, parametrization="mean",
  to_return="total_ccovs")
```

---

cond_moment_plot *Conditional mean or variance plot for a GMVAR model*

Description

`cond_moment_plot` plots the one-step in-sample conditional means/variances of the model along with the individual time series contained in the model (e.g. the time series the model was fitted to). Also plots the regimewise conditional means/variances multiplied with mixing weights.

Usage

```
cond_moment_plot(
  gmvar,
  which_moment = c("mean", "variance"),
  grid = FALSE,
  ...
)
```

Arguments

gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.
which_moment	should conditional means or variances be plotted?
grid	add grid to the plots?
...	additional paramters passed to grid(...) plotting the grid if grid == TRUE.

Details

The conditional mean plot works best if the data contains positive values only. acf from the package stats and the plot method for class 'acf' objects is employed.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

profile_logliks, fitGMVAR, GMVAR, quantile_residual_tests, LR_test, Wald_test, diagnostic_plot

Examples

```
# These examples use the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(2,2), d=2 model:
params222 <-  c(1.386, -0.765, 1.314, 0.145, 0.094, 1.292, -0.389,
 -0.070, -0.109, -0.281, 0.920, -0.025, 4.839, 1.005, 5.928, 1.248,
  0.077, -0.040, 1.266, -0.272, -0.074, 0.034, -0.313, 5.855, 3.570,
  9.838, 0.740)
mod222 <- GMVAR(data, p=2, M=2, params=params222)

cond_moment_plot(mod222, which_moment="mean")
cond_moment_plot(mod222, which_moment="variance")
cond_moment_plot(mod222, which_moment="mean", grid=TRUE, lty=2)
```

diagnostic_plot *Quantile residual diagnostic plot for a GMVAR model*

Description

diagnostic_plot plots a multivariate quantile residual diagnostic plot for either autocorrelation, conditional heteroskedasticity, or normality, or simply draws the quantile residual time series.

Usage

```
diagnostic_plot(
  gmvar,
  type = c("all", "series", "ac", "ch", "norm"),
  maxlag = 10,
  wait_time = 4
)
```

Arguments

gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.
type	which type of diagnostic plot should be plotted? • "all" all below sequentially. • "series" the quantile residual time series. • "ac" the quantile residual autocorrelation and cross-correlation functions. • "ch" the squared quantile residual autocorrelation and cross-correlation functions. • "norm" the quantile residual histogram with theoretical standard normal density (dashed line) and standard normal QQ-plots.
maxlag	the maximum lag considered in types "ac" and "ch".
wait_time	if type == all how many seconds to wait before showing next figure?

Details

Auto- and cross-correlations (types "ac" and "ch") are calculated with the function acf from the package stats and the plot method for class 'acf' objects is employed.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Kalliovirta L. and Saikkonen P. 2010. Reliable Residuals for Multivariate Nonlinear Time Series Models. *Unpublished Revision of HECER Discussion Paper No. 247*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

profile_logliks, fitGMVAR, GMVAR, quantile_residual_tests, LR_test, Wald_test, cond_moment_plot, acf, density, predict.gmvar

Examples

```
# These examples use the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(1,2), d=2 model:
params122 <- c(0.623, -0.129, 0.959, 0.089, -0.006, 1.006, 1.746,
 0.804, 5.804, 3.245, 7.913, 0.952, -0.037, -0.019, 0.943, 6.926,
 3.982, 12.135, 0.789)
mod122 <- GMVAR(data, p=1, M=2, params=params122)
diagnostic_plot(mod122, type="series")
diagnostic_plot(mod122, type="ac")

# GMVAR(2,2), d=2 model:
params222 <-  c(1.386, -0.765, 1.314, 0.145, 0.094, 1.292, -0.389,
 -0.070, -0.109, -0.281, 0.920, -0.025, 4.839, 1.005, 5.928, 1.248,
  0.077, -0.040, 1.266, -0.272, -0.074, 0.034, -0.313, 5.855, 3.570,
  9.838, 0.740)
mod222 <- GMVAR(data, p=2, M=2, params=params222)
diagnostic_plot(mod222, type="ch")
diagnostic_plot(mod222, type="norm")

# GMVAR(2,2), d=2 model with AR-parameters restricted to be
# the same for both regimes:
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
params222c <- c(1.031, 2.356, 1.786, 3.000, 1.250, 0.060, 0.036,
 1.335, -0.290, -0.083, -0.047, -0.356, 0.934, -0.152, 5.201, 5.883,
 3.560, 9.799, 0.368)
mod222c <- GMVAR(data, p=2, M=2, params=params222c, constraints=C_mat)
diagnostic_plot(mod222c, wait_time=0.1)
diagnostic_plot(mod222c, type="ac", maxlag=12)
```

---

diag_Omegas *Simultaneously diagonalize two covariance matrices*

Description

diag_Omegas Simultaneously diagonalizes two covariance matrices using eigenvalue decomposition.

Usage

```
diag_Omegas(Omega1, Omega2)
```

Arguments

Omega1	a positive definite (dxd) covariance matrix $(d > 1)$
Omega2	another positive definite (dxd) covariance matrix

Details

See the return value and Muirhead (1982), Theorem A9.9 for details.

Value

Returns a length $d^2 + d$ vector where the first d^2 elements are $vec(W)$ with the columns of W being (specific) eigenvectors of the matrix $\Omega_2\Omega_1^{-1}$ and the rest d elements are the corresponding eigenvalues "lambdas". The result satisfies $WW' = Omega1$ and $Wdiag(lambdas)W' = Omega2$.

If Omega2 is not supplied, returns a vectorized symmetric (and pos. def.) square root matrix of Omega1.

Warning

No argument checks! Does not work with dimension $d = 1$!

References

- Muirhead R.J. 1982. Aspects of Multivariate Statistical Theory, *Wiley*.

Examples

```
d <- 2
W0 <- matrix(1:(d^2), nrow=2)
lambdas0 <- 1:d
(Omg1 <- W0%*%t(W0))
(Omg2 <- W0%*%diag(lambdas0)%*%t(W0))
res <- diag_Omegas(Omg1, Omg2)
W <- matrix(res[1:(d^2)], nrow=d, byrow=FALSE)
tcrossprod(W) # == Omg1
lambdas <- res[(d^2 + 1):(d^2 + d)]
W%*%diag(lambdas)%*%t(W) # == Omg2
```

---

dlogmultinorm *Calculate logarithms of multiple multivariate normal densities with varying mean and constant covariance matrix*

Description

dlogmultinorm calculates logarithms of multiple multivariate normal densities with varying mean and constant covariance matrix.

Usage

```
dlogmultinorm(y, mu, Omega)
```

Arguments

y	dimension (Txk) matrix where each row is a k-dimensional random vector
mu	dimension (Txk) matrix where each row is the mean of the k-dimensional random vector in corresponding row of y.
Omega	the (kxk) covariance matrix Omega.

Value

Returns a size $(Tx1)$ vector containing the multinormal densities in logarithm.

---

eurusd — *Euro area and U.S. long-term government bond yields and Euro-U.S. dollar exchange rate.*

Description

A dataset containing time series of the difference between the monthly Euro area and U.S. long-term government bond yields and monthly average Euro - U.S. dollar exchange rate. The data covers the time period January 1989 - December 2009 with monthly frequency. This is the same data (in non-scaled form) that is used by Kalliovirta et. al. (2016).

Usage

```
eurusd
```

Format

A numeric matrix of class `'ts'` with 252 rows and 2 columns with one time series in each column:

First column: The difference between the monthly Euro area and U.S. long-term government bond yields (10 year maturity, i_euro - i_us), from January 1989 to December 2009. calculated by the ECB and the Federal Reserve Board; prior to 2001, the Euro area data refer to the "EU11" countries, and afterwards with changing composition eventually to the "EU17" by the end of the data period.

Second column: Monthly average Euro - U.S. dollar exchange rate, from January 1989 to December 2009. Based on the ECU - USD exchange rate prior to 1999.

Source

OECD Statistics

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Kalliovirta L. and Saikkonen P. 2010. Reliable Residuals for Multivariate Nonlinear Time Series Models. *Unpublished Revision of HECER Discussion Paper No. 247*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`fitGMVAR` *Two-phase maximum likelihood estimation of a GMVAR model*

Description

`fitGMVAR` estimates a GMVAR model in two phases: in the first phase it uses a genetic algorithm to find starting values for a gradient based variable metric algorithm, which it then uses to finalize the estimation in the second phase. Parallel computing is utilized to perform multiple rounds of estimations in parallel.

Usage

```
fitGMVAR(
  data,
  p,
  M,
  conditional = TRUE,
  parametrization = c("intercept", "mean"),
  constraints = NULL,
  structural_pars = NULL,
  ncalls = round(10 + 9 * log(M)),
  ncores = min(2, ncalls, parallel::detectCores()),
  maxit = 300,
  seeds = NULL,
  print_res = TRUE,
  ...
)
```

Arguments

`data`	a matrix or class `'ts'` object with `d>1` columns. Each column is taken to represent a single time series. `NA` values are not supported.
`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`conditional`	a logical argument specifying whether the conditional or exact log-likelihood function

`parametrization`
: `"mean"` or `"intercept"` determining whether the model is parametrized with regime means μ_m or intercept parameters $\phi_{m,0}$, m=1,...,M.

`constraints`
: a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`
: If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

  - `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
  - `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

  See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

`ncalls`
: the number of estimation rounds that should be performed.

`ncores`
: the number CPU cores to be used in parallel computing.

`maxit`
: the maximum number of iterations in the variable metric algorithm.

`seeds`
: a length `ncalls` vector containing the random number generator seed for each call to the genetic algorithm, or `NULL` for not initializing the seed. Exists for creating reproducible results.

`print_res`
: should summaries of estimation results be printed?

`...`
: additional settings passed to the function `GAfit` employing the genetic algorithm.

Details

Because of complexity and multimodality of the log-likelihood function, it's **not certain** that the estimation algorithms will end up in the global maximum point. It's expected that most of the estimation rounds will end up in some local maximum or saddle point instead. Therefore, a (sometimes large) number of estimation rounds is required for reliable results. Because of the nature of the model, the estimation may fail especially in the cases where the number of mixture components is chosen too large.

The estimation process is computationally heavy and it might take considerably long time for large models with large number of observations. If the iteration limit `maxit` in the variable metric algorithm is reached, one can continue the estimation by iterating more with the function `iterate_more`.

Alternatively, one may use the found estimates as starting values for the genetic algorithm and and employ another round of estimation (see `?GAfit` how to set up an initial population with the dot parameters).

The code of the genetic algorithm is mostly based on the description by *Dorsey and Mayer (1995)* but it includes some extra features that were found useful for this particular estimation problem. For instance, the genetic algorithm uses a slightly modified version of the individually adaptive crossover and mutation rates described by *Patnaik and Srinivas (1994)* and employs (50%) fitness inheritance discussed by *Smith, Dike and Stegmann (1995)*.

The gradient based variable metric algorithm used in the second phase is implemented with function `optim` from the package `stats`.

Finally, note that the structural models are even more difficult to estimate than the reduced form models due to the different parametrization of the covariance matrices. If necessary, an initial population may be constructed for the genetic algorithm based on the estimation results of a reduced form model. It does not seem unambiguous, however, how to do that so that the (structural) parameter constraints are satisfied. Also, be aware that if the lambda parameters are constrained in any other way than by restricting some of them to be identical, the parameter "lambda_scale" of the genetic algorithm (see `?GAfit`) needs to be carefully adjusted accordingly. Be aware that if a structural model is considered and the lambda parameters are constrained in some other way than constraining some of them to be identical, the settings of the genetic algorithm may have to be adjusted.

Value

Returns an object of class `'gmvar'` defining the estimated (reduced form or structural) GMVAR model. Multivariate quantile residuals (Kalliovirta and Saikkonen 2010) are also computed and included in the returned object. In addition, the returned object contains the estimates and log-likelihood values from all the estimation rounds performed. The estimated parameter vector can be obtained at `gmvar$params` (and corresponding approximate standard errors at `gmvar$std_errors`) and it is...

For unconstrained models: ...a size $((M(pd^2+d+d(d+1)/2+1)-1)x1)$ vector that has form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}$,$\phi_m, \sigma_m)$
- ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: ...a size $((M(d + d(d + 1)/2 + 1) + q - 1)x1)$ vector that has form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \psi$, $\sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: ...a vector that has the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M, \alpha_1, ..., \alpha_{M-}$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

Remark that the first autocovariance/correlation matrix in `$uncond_moments` is for the lag zero, the second one for the lag one, etc.

S3 methods

The following S3 methods are supported for class `'gmvar'`: `logLik`, `residuals`, `print`, `summary`, `predict` and `plot`.

References

- Dorsey R. E. and Mayer W. J. 1995. Genetic algorithms for estimation problems with multiple optima, nondifferentiability, and other irregular features. *Journal of Business & Economic Statistics*, **13**, 53-66.
- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Kalliovirta L. and Saikkonen P. 2010. Reliable Residuals for Multivariate Nonlinear Time Series Models. *Unpublished Revision of HECER Discussion Paper No. 247*.
- Patnaik L.M. and Srinivas M. 1994. Adaptive Probabilities of Crossover and Mutation in Genetic Algorithms. *Transactions on Systems, Man and Cybernetics* **24**, 656-667.
- Smith R.E., Dike B.A., Stegmann S.A. 1995. Fitness inheritance in genetic algorithms. *Proceedings of the 1995 ACM Symposium on Applied Computing*, 345-350.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

`GMVAR`, `iterate_more`, `predict.gmvar`, `profile_logliks`, `simulateGMVAR`, `quantile_residual_tests`, `print_std_errors`, `swap_parametrization`, `get_gradient`, `GIRF`, `LR_test`, `Wald_test`, `gmvar_to_sgmvar`, `reorder_W_columns`, `swap_W_signs`, `cond_moment_plot`

Examples

```
## These are long running examples that use parallel computing!

# These examples use the data 'eurusd' which comes with the
```

```
# package, but in a scaled form (similar to Kalliovirta et al. 2016).
data(eurusd, package="gmvarkit")
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(1,2) model: 10 estimation rounds with seeds set
# for reproducibility
fit12 <- fitGMVAR(data, p=1, M=2, ncalls=10, seeds=1:10)
fit12
plot(fit12)
summary(fit12)
print_std_errors(fit12)
profile_logliks(fit12)

# Structural GMVAR(1,2) model identified with sign
# constraints. The sign constraints (which fully identify
# the shocks) are in line with the reduced form model,
# so the maximized loglikelihood is the same.
W_122 <- matrix(c(1, NA, -1, 1), nrow=2)
fit12s <- fitGMVAR(data, p=1, M=2, structural_pars=list(W=W_122),
  ncalls=10, seeds=1:10)
fit12s

# GMVAR(2,2) model with mean parametrization
fit22 <- fitGMVAR(data, p=2, M=2, parametrization="mean",
                  ncalls=16, seeds=1:16)
fit22

# Structural GMVAR(2,2) model with the lambda parameters restricted
# to be identical (in the second regime) and the shocks identified
# with diagonal of the B-matrix normalized positive and one zero constraint.
# The resulting model has error term covariance matrices that are
# multiplicatives of each other, while the identification equals to
# identification through Cholesky decomposition.
W_222 <- matrix(c(1, NA, 0, 1), nrow=2)
C_lambda_222 <- matrix(c(1, 1), nrow=2)
fit22s <- fitGMVAR(data, p=2, M=2, structural_pars=list(W=W_222, C_lambda=C_lambda_222),
  ncalls=20, seeds=1:20)
fit22s

# GMVAR(2,2) model with autoregressive parameters restricted
# to be the same for both regimes
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
fit22c <- fitGMVAR(data, p=2, M=2, constraints=C_mat)
fit22c

# GMVAR(2,2) model with autoregressive parameters restricted
# to be the same for both regimes and non-diagonl elements
# the coefficient matrices constrained to zero. Estimation
# with only 10 estimation rounds.
tmp <- matrix(c(1, rep(0, 10), 1, rep(0, 8), 1, rep(0, 10), 1),
 nrow=2*2^2, byrow=FALSE)
C_mat2 <- rbind(tmp, tmp)
```

```
fit22c2 <- fitGMVAR(data, p=2, M=2, constraints=C_mat2)
fit22c2
```

`format_valuef` *Function factory for value formatting*

Description

`format_valuef` is a function factory for formatting values with certain number of digits.

Usage

```
format_valuef(digits)
```

Arguments

`digits`	the number of decimals to print

Value

Returns a function that takes an atomic vector as argument and returns it formatted to character with `digits` decimals.

`form_boldA` *Form the $((dp)x(dp))$ "bold A" matrices related to the VAR processes*

Description

`form_boldA` creates the "bold A" coefficient matrices related to VAR processes.

Usage

```
form_boldA(p, M, d, all_A)
```

Arguments

`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`d`	the number of time series in the system.
`all_A`	4D array containing all coefficient matrices $A_{m,i}$, obtained from `pick_allA`.

Value

Returns 3D array containing the $((dp)x(dp))$ "bold A" matrices related to each component VAR-process. The matrix A_m can be obtained by choosing `[,,m]`.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`GAfit` *Genetic algorithm for preliminary estimation of a GMVAR model*

Description

`GAfit` estimates the specified GMVAR model using a genetic algorithm. It's designed to find starting values for gradient based methods.

Usage

```
GAfit(
  data,
  p,
  M,
  conditional = TRUE,
  parametrization = c("intercept", "mean"),
  constraints = NULL,
  structural_pars = NULL,
  ngen = 200,
  popsize,
  smart_mu = min(100, ceiling(0.5 * ngen)),
  initpop = NULL,
  mu_scale,
  mu_scale2,
  omega_scale,
  W_scale,
  lambda_scale,
  ar_scale = 1,
  regime_force_scale = 1,
  red_criteria = c(0.05, 0.01),
  to_return = c("alt_ind", "best_ind"),
  minval,
  seed = NULL
)
```

Arguments

`data` a matrix or class `'ts'` object with `d>1` columns. Each column is taken to represent a single time series. `NA` values are not supported.

`p` a positive integer specifying the autoregressive order of the model.

`M` a positive integer specifying the number of mixture components.

`conditional` a logical argument specifying whether the conditional or exact log-likelihood function

`parametrization`

`"mean"` or `"intercept"` determining whether the model is parametrized with regime means μ_m or intercept parameters $\phi_{m,0}$, m=1,...,M.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

`ngen` a positive integer specifying the number of generations to be ran through in the genetic algorithm.

`popsize` a positive even integer specifying the population size in the genetic algorithm. Default is `10*n_params`.

`smart_mu` a positive integer specifying the generation after which the random mutations in the genetic algorithm are "smart". This means that mutating individuals will mostly mutate fairly close (or partially close) to the best fitting individual (which has the least regimes with time varying mixing weights practically at zero) so far.

`initpop` a list of parameter vectors from which the initial population of the genetic algorithm will be generated from. The parameter vectors should be...

For unconstrained models: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where:

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where:

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$. Here C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M)$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`mu_scale` a size $(dx1)$ vector defining **means** of the normal distributions from which each mean parameter μ_m is drawn from in random mutations. Default is `colMeans(data)`. Note that mean-parametrization is always used for optimization in `GAfit` - even when `parametrization=="intercept"`. However, input (in `initpop`) and output (return value) parameter vectors can be intercept-parametrized.

`mu_scale2` a size $(dx1)$ strictly positive vector defining **standard deviations** of the normal distributions from which each mean parameter μ_m is drawn from in random mutations. Default is `2*sd(data[,i]),i=1,..,d`.

`omega_scale` a size $(dx1)$ strictly positive vector specifying the scale and variability of the random covariance matrices in random mutations. The covariance matrices are drawn from (scaled) Wishart distribution. Expected values of the random covariance matrices are `diag(omega_scale)`. Standard deviations of the diagonal elements are `sqrt(2/d)*omega_scale[i]` and for non-diagonal elements they are `sqrt(1/d*omega_scale[i]*omega_scale[j])`. Note that for `d>4` this scale may need to be chosen carefully. Default in `GAfit` is `var(stats::ar(data[,i],order.max=10)$resid` This argument is ignored if structural model is considered.

`W_scale` a size $(dx1)$ strictly positive vector partly specifying the scale and variability of the random covariance matrices in random mutations. The elements of the ma-

trix W are drawn independently from such normal distributions that the expectation of the main **diagonal** elements of the first regime's error term covariance matrix $\Omega_1 = WW'$ is `W_scale`. The distribution of Ω_1 will be in some sense like a Wishart distribution but with the columns (elements) of W obeying the given constraints. The constraints are accounted for by setting the element to be always zero if it is subject to a zero constraint and for sign constraints the absolute value or negative the absolute value are taken, and then the variances of the elements of W are adjusted accordingly. This argument is ignored if reduced form model is considered.

`lambda_scale` a length $M-1$ vector specifying the **standard deviation** of the mean zero normal distribution from which the eigenvalue λ_{mi} parameters are drawn from in random mutations. As the eigenvalues should always be positive, the absolute value is taken. The elements of `lambda_scale` should be strictly positive real numbers with the $m-1$th element giving the degrees of freedom for the mth regime. The expected value of the main **diagonal** elements ij of the mth $(m > 1)$ error term covariance matrix will be `W_scale[i]*(d-n_i)^(-1)*sum(lambdas*ind_fun)` where the $(dx1)$ vector `lambdas` is drawn from the absolute value of the t-distribution, `n_i` is the number of zero constraints in the ith row of W and `ind_fun` is an indicator function that takes the value one iff the ijth element of W is not constrained to zero. Basically, larger lambdas (or smaller degrees of freedom) imply larger variance.

If the lambda parameters are **constrained** with the $(d(M-1)xr)$ constraint matrix C_lambda, then provide a length r vector specifying the standard deviation of the (absolute value of the) mean zero normal distribution each of the γ parameters are drawn from (the γ is a $(rx1)$ vector). The expected value of the main diagonal elements of the covariance matrices then depend on the constraints.

This argument is ignored if $M == 1$ or a reduced form model is considered. Default is `rep(3,times=M-1)` if lambdas are not constrained and `rep(3,times=r)` if lambdas are constrained.

As with omega_scale and W_scale, this argument should be adjusted carefully if specified by hand. **NOTE** that if lambdas are constrained in some other way than restricting some of them to be identical, this parameter should be adjusted accordingly in order to the estimation succeed!

`ar_scale` a positive real number adjusting how large AR parameter values are typically generated in some random mutations. See the function `random_coefmats2` for details. This is ignored when estimating constrained models.

`regime_force_scale`

a non-negative real number specifying how much should natural selection favour individuals with less regimes that have almost all mixing weights (practically) at zero. Set to zero for no favouring or large number for heavy favouring. Without any favouring the genetic algorithm gets more often stuck in an area of the parameter space where some regimes are wasted, but with too much favouring the best genes might never mix into the population and the algorithm might converge poorly. Default is `1` and it gives $2x$ larger surviving probability weights for individuals with no wasted regimes compared to individuals with one wasted regime. Number `2` would give $3x$ larger probability weights etc.

`red_criteria` a length 2 numeric vector specifying the criteria that is used to determine whether a regime is redundant (or "wasted") or not. Any regime `m` which satisfies `sum(mixingWeights[,m]`

	> red_criteria[1]) < red_criteria[2]*n_obs will be considered "redundant". One should be careful when adjusting this argument (set c(0,0) to fully disable the 'redundant regime' features from the algorithm).
to_return	should the genetic algorithm return the best fitting individual which has "positive enough" mixing weights for as many regimes as possible ("alt_ind") or the individual which has the highest log-likelihood in general ("best_ind") but might have more wasted regimes?
minval	a real number defining the minimum value of the log-likelihood function that will be considered. Values smaller than this will be treated as they were minval and the corresponding individuals will never survive. The default is -(10^(ceiling(log10(n_obs)) + d) -1).
seed	a single value, interpreted as an integer, or NULL, that sets seed for the random number generator in the beginning of the function call. If calling GAfit from fitGMVAR, use the argument seeds instead of passing the argument seed.

Details

The core of the genetic algorithm is mostly based on the description by *Dorsey and Mayer (1995)*. It utilizes a slightly modified version of the individually adaptive crossover and mutation rates described by *Patnaik and Srinivas (1994)* and employs (50%) fitness inheritance discussed by *Smith, Dike and Stegmann (1995)*.

By "redundant" or "wasted" regimes we mean regimes that have the time varying mixing weights practically at zero for almost all t. A model including redundant regimes would have about the same log-likelihood value without the redundant regimes and there is no purpose to have redundant regimes in a model.

Value

Returns the estimated parameter vector which has the form described in initpop.

References

- Ansley C.F., Kohn R. 1986. A note on reparameterizing a vector autoregressive moving average model to enforce stationarity. *Journal of statistical computation and simulation*, **24**:2, 99-106.
- Dorsey R. E. and Mayer W. J. 1995. Genetic algorithms for estimation problems with multiple optima, nondifferentiability, and other irregular features. *Journal of Business & Economic Statistics*, **13**, 53-66.
- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Patnaik L.M. and Srinivas M. 1994. Adaptive Probabilities of Crossover and Mutation in Genetic Algorithms. *Transactions on Systems, Man and Cybernetics* **24**, 656-667.
- Smith R.E., Dike B.A., Stegmann S.A. 1995. Fitness inheritance in genetic algorithms. *Proceedings of the 1995 ACM Symposium on Applied Computing*, 345-350.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

@export

`get_boldA_eigens` *Calculate absolute values of the eigenvalues of the "bold A" matrices containing the AR coefficients*

Description

`get_boldA_eigens` calculates absolute values of the eigenvalues of the "bold A" matrices containing the AR coefficients for each mixture component.

Usage

```
get_boldA_eigens(gmvar)
```

Arguments

`gmvar`	an object of class `'gmvar'` created with `fitGMVAR` or `GMVAR`.

Value

Returns a matrix with $d * p$ rows and M columns - one column for each regime. The mth column contains the absolute values (or modulus) of the eigenvalues of the "bold A" matrix containing the AR coefficients correspinding to regime m.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

Examples

```
params222 <- c(-11.904, 154.684, 1.314, 0.145, 0.094, 1.292, -0.389,
 -0.070, -0.109, -0.281, 0.920, -0.025, 4.839, 11.633, 124.983, 1.248,
  0.077, -0.040, 1.266, -0.272, -0.074, 0.034, -0.313, 5.855, 3.570,
  9.838, 0.740)
mod222 <- GMVAR(d=2, p=2, M=2, params=params222, parametrization="mean")
get_boldA_eigens(mod222)
```

get_IC *Calculate AIC, HQIC, and BIC*

Description

`get_IC` calculates the information criteria values AIC, HQIC, and BIC.

Usage

```
get_IC(loglik, npars, obs)
```

Arguments

`loglik`	log-likelihood value
`npars`	number of (freely estimated) parameters in the model
`obs`	numbers of observations with starting values excluded for conditional models.

Details

Note that for conditional models with different autoregressive order p the information criteria values are **NOT** comparable.

Value

Returns a data frame containing the information criteria values.

get_minval *Returns the default smallest allowed log-likelihood for given data.*

Description

`get_minval` returns the default smallest allowed log-likelihood for given data.

Usage

```
get_minval(data)
```

Arguments

`data`	a matrix or class `'ts'` object with `d>1` columns. Each column is taken to represent a single time series. `NA` values are not supported.

Details

This function exists to avoid dublication inside the package.

Value

Returns `-(10^(ceiling(log10(nrow(data)) + ncol(data))) -1)`

See Also

`fitGMVAR`, `GAfit`

`get_omega_eigens` *Calculate the eigenvalues of the "Omega" error term covariance matrices*

Description

`get_omega_eigens` calculates the eigenvalues of the "Omega" error term covariance matrices for each mixture component.

Usage

```
get_omega_eigens(gmvar)
```

Arguments

`gmvar`	an object of class `'gmvar'` created with `fitGMVAR` or `GMVAR`.

Value

Returns a matrix with d rows and M columns - one column for each regime. The mth column contains the eigenvalues of the "Omega" error term covariance matrix of the mth regime.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

Examples

```
params222 <- c(-11.904, 154.684, 1.314, 0.145, 0.094, 1.292, -0.389,
 -0.070, -0.109, -0.281, 0.920, -0.025, 4.839, 11.633, 124.983, 1.248,
  0.077, -0.040, 1.266, -0.272, -0.074, 0.034, -0.313, 5.855, 3.570,
  9.838, 0.740)
mod222 <- GMVAR(d=2, p=2, M=2, params=params222, parametrization="mean")
get_omega_eigens(mod222)
```

get_regime_autocovs *Calculate regimewise autocovariance matrices*

Description

get_regime_autocovs calculates the first p regimewise autocovariance matrices $\Gamma_m(j)$ for the given GMVAR model.

Usage

```
get_regime_autocovs(gmvar)
```

Arguments

gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.

Value

Returns an $(dxdxp + 1xM)$ array containing the first p regimewise autocovariance matrices. The subset [,,j,m] contains the j-1:th lag autocovariance matrix of the m:th regime.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

Other moment functions: cond_moments(), get_regime_means(), uncond_moments()

Examples

```
# GMVAR(1,2), d=2 model:
params122 <- c(0.623, -0.129, 0.959, 0.089, -0.006, 1.006, 1.746,
 0.804, 5.804, 3.245, 7.913, 0.952, -0.037, -0.019, 0.943, 6.926,
 3.982, 12.135, 0.789)
mod122 <- GMVAR(p=1, M=2, d=2, params=params122)
get_regime_autocovs(mod122)

# GMVAR(2,2), d=2 model with AR-parameters restricted to be
# the same for both regimes:
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
params222c <- c(1.031, 2.356, 1.786, 3.000, 1.250, 0.060, 0.036,
 1.335, -0.290, -0.083, -0.047, -0.356, 0.934, -0.152, 5.201, 5.883,
 3.560, 9.799, 0.368)
```

```
mod222c <- GMVAR(p=2, M=2, d=2, params=params222c, constraints=C_mat)
get_regime_autocovs(mod222c)

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(1.03, 2.36, 1.79, 3, 1.25, 0.06, 0.04, 1.34, -0.29,
 -0.08, -0.05, -0.36, 1.2, 0.05, 0.05, 1.3, -0.3, -0.1, -0.05, -0.4,
  0.89, 0.72, -0.37, 2.16, 7.16, 1.3, 0.37)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
mod222s <- GMVAR(p=2, M=2, d=2, params=params222s, structural_pars=list(W=W_222))
get_regime_autocovs(mod222s)
```

`get_regime_autocovs_int` *Calculate regimewise autocovariance matrices*

Description

`get_regime_autocovs_int` calculates the regimewise autocovariance matrices $\Gamma_m(j)$ $j = 0, 1, ..., p$ for the given GMVAR model.

Usage

```
get_regime_autocovs_int(
  p,
  M,
  d,
  params,
  constraints = NULL,
  structural_pars = NULL
)
```

Arguments

`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`d`	the number of time series in the system.
`params`	a real valued vector specifying the parameter values. **For unconstrained models:** Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where • $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$ • ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$ • and $\sigma_m = vech(\Omega_m)$, m=1,...,M. **For constrained models:** Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where • ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form θ= ($\phi_{1,0}$, ..., $\phi_{M,0}$,ϕ_1, ...,ϕ_M, $vec(W)$,λ_2, ...,λ_M where

- λ_m = (λ_{m1}, ..., λ_{md}) contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace ϕ_1, ..., ϕ_M with ψ $(qx1)$ that satisfies (ϕ_1, ..., ϕ_M) = $C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace λ_2, ...,λ_M with γ $(rx1)$ that satisfies (λ_2, ..., λ_M) = $C_\lambda\gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form (ϕ_1, ...,ϕ_M) =$C\psi$, where ϕ_m= ($vec(A_{m,1})$, ..., $vec(A_{m,p})$(pd^2x1), $m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies (λ_2, ..., λ_M) = $C_\lambda\gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

Returns an $(dxdxp + 1xM)$ array containing the first p regimewise autocovariance matrices. The subset `[,,j,m]` contains the j-1:th lag autocovariance matrix of the m:th regime.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`get_regime_means` *Calculate regime means μ_m*

Description

`get_regime_means` calculates regime means $\mu_m = (I - \sum A_{m,i})^(- 1))$ for the given GMVAR model.

Usage

```
get_regime_means(gmvar)
```

Arguments

`gmvar`	an object of class `'gmvar'` created with `fitGMVAR` or `GMVAR`.

Value

Returns a (dxM) matrix containing regime mean μ_m in the m:th column, $m = 1, .., M$.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

`uncond_moments`, `get_regime_autocovs`, `cond_moments`

Other moment functions: `cond_moments()`, `get_regime_autocovs()`, `uncond_moments()`

Examples

```
# These examples use the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(1,2), d=2 model:
params122 <- c(0.623, -0.129, 0.959, 0.089, -0.006, 1.006, 1.746,
 0.804, 5.804, 3.245, 7.913, 0.952, -0.037, -0.019, 0.943, 6.926,
 3.982, 12.135, 0.789)
mod122 <- GMVAR(data, p=1, M=2, params=params122)
mod122
get_regime_means(mod122)

# GMVAR(2,2), d=2 model with mean-parametrization:
params222 <- c(-11.904, 154.684, 1.314, 0.145, 0.094, 1.292, -0.389,
 -0.070, -0.109, -0.281, 0.920, -0.025, 4.839, 11.633, 124.983, 1.248,
  0.077, -0.040, 1.266, -0.272, -0.074, 0.034, -0.313, 5.855, 3.570,
  9.838, 0.740)
mod222 <- GMVAR(data, p=2, M=2, params=params222, parametrization="mean")
mod222
get_regime_means(mod222)

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(1.03, 2.36, 1.79, 3, 1.25, 0.06, 0.04, 1.34, -0.29,
 -0.08, -0.05, -0.36, 1.2, 0.05, 0.05, 1.3, -0.3, -0.1, -0.05, -0.4,
  0.89, 0.72, -0.37, 2.16, 7.16, 1.3, 0.37)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
mod222s <- GMVAR(data, p=2, M=2, params=params222s, structural_pars=list(W=W_222))
mod222s
get_regime_means(mod222s)
```

---

get_regime_means_int *Calculate regime means μ_m*

Description

get_regime_means calculates regime means $\mu_m = (I - \sum A)^(-1))$ from the given parameter vector.

Usage

```
get_regime_means_int(
  p,
  M,
  d,
  params,
  parametrization = c("intercept", "mean"),
  constraints = NULL,
```

```
  structural_pars = NULL
)
```

Arguments

p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
d	the number of time series in the system.
params	a real valued vector specifying the parameter values.

For unconstrained models: Should be size $((M(pd^2+d+d(d+1)/2+1)-1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace λ_2, ...,λ_M with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by ***Kalliovirta, Meitz and Saikkonen (2016)*** introducing the GMVAR model.

parametrization	`"mean"` or `"intercept"` determining whether the model is parametrized with regime means μ_m or intercept parameters $\phi_{m,0}$, m=1,...,M.
constraints	a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p}))(pd^2x1), m = 1, ..., M$, contains the

coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

Returns a (dxM) matrix containing regime mean μ_m in the m:th column, $m = 1, .., M$.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`get_test_Omega` *Compute covariance matrix Omega used in quantile residual tests*

Description

`get_test_Omega` computes the covariance matrix Omega used in the quantile residuals tests described by *Kalliovirta and Saikkonen 2010*.

Usage

```
get_test_Omega(
  data,
  p,
  M,
  params,
  conditional,
  parametrization,
  constraints,
  structural_pars = NULL,
  g,
  dim_g
)
```

Arguments

data	a matrix or class 'ts' object with d>1 columns. Each column is taken to represent a single time series. NA values are not supported.
p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
params	a real valued vector specifying the parameter values.

For unconstrained models: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d + d(d+1)/2 + 1) + q - 1)x1)$ and have form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M)$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If

parametrization=="mean", just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`conditional` a logical argument specifying whether the conditional or exact log-likelihood function should be used.

`parametrization`
"mean" or "intercept" determining whether the model is parametrized with regime means μ_m or intercept parameters $\phi_{m,0}$, m=1,...,M.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`
If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

`g` function g specifying the transformation.

`dim_g` output dimension of the transformation g.

Value

Returns the covariance matrix Omega described by *Kalliovirta and Saikkonen 2010*.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Kalliovirta L. and Saikkonen P. 2010. Reliable Residuals for Multivariate Nonlinear Time Series Models. *Unpublished Revision of HECER Discussion Paper No. 247*.

- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`get_unconstrained_structural_pars` *Get structural parameters that indicate there are no constraints*

Description

`get_unconstrained_struct_pars` return structural parameters that indicate there are no constraints (except possibly sign constraints).

Usage

```
get_unconstrained_structural_pars(structural_pars = NULL)
```

Arguments

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Details

Intended to be called after calling the function `reform_constrained_pars` to avoid remove the constraints again in any further function calls as this will create bugs. Sign constraints are irrelevant in this context.

Value

Returns a list with `$W` being (dxd) matrix of ones and `$C_lambda` being `NULL`. If the supplied argument is `NULL`, returns `NULL`.

Warning

No argument checks!

GIRF *Estimate generalized impulse response function for a structural GMVAR model.*

Description

GIRF estimate generalized impulse response function for a structural GMVAR model.

Usage

```
GIRF(
  gmvar,
  variables,
  shock_size,
  N = 30,
  R1 = 250,
  R2 = 250,
  init_regimes = 1:M,
  init_values = NULL,
  ci = c(0.95, 0.8),
  include_mixweights = TRUE,
  ncores = min(2, parallel::detectCores()),
  seeds = NULL
)

## S3 method for class 'girf'
plot(x, add_grid = FALSE, ...)

## S3 method for class 'girf'
print(x, ..., digits = 2, N_to_print)
```

Arguments

gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.
variables	a numeric vector of length at most d (=ncol(data)) and elements in $1, ..., d$ specifying the variables for which the GIRF should be estimated.
shock_size	a vector with the same length as variables specifying the size of the structural shock for each variable. By default, the shock size is one, which is then amplified by the B-matrix according to the conditional standard deviation of the model.
N	a positive integer specifying the horizon how far ahead should the generalized impulse responses be calculated?
R1	the number of repetitions used to estimate GIRF for each initial value?
R2	the number of initial values to be drawn from a stationary distribution of the process or of a specific regime? The confidence bounds will be sample quantiles of the GIRFs based on different initial values. Ignored if the argument init_value is specified.

`init_regimes` a numeric vector of length at most M and elements in $1, ..., M$ specifying the regimes from which the initial values should be generated from. The initial values will be generated from a mixture distribution with the mixture components being the stationary distirbutions of the specific regimes and the (proportiional) mixing weights given by the mixing weight parameters of those regimes. Note that if `init_regimes=1:M`, the initial values are generated from the stationary distribution of the process and if `init_regimes=m`, the initial value are generated from the stationary distribution of the mth regime. Ignored if `init_value` is specified.

`init_values` a matrix or a multivariate class `'ts'` object with d columns and at least p rows specifying an initial value for the GIRF. The last p rows are taken to be the initial value assuming that the **last** row is the most recent observation.

`ci` a numeric vector with elements in $(0, 1)$ specifying the confidence levels of the confidence intervals.

`include_mixweights` should the generalized impulse response be calculated for the mixing weights as well? `TRUE` or `FALSE`.

`ncores` the number CPU cores to be used in parallel computing. Only single core computing is supported if an initial value is specified (and the GIRF won't thus be estimated multiple times).

`seeds` a length `R2` vector containing the random number generator seed for estimation of each GIRF. A single number of an initial value is specified. or `NULL` for not initializing the seed. Exists for creating reproducible results.

`x` object of class `'girf'` generated by the function `GIRF`.

`add_grid` should grid be added to the plots?

`...` arguments passed to `grid` which plots grid to the figure.

`digits` the number of decimals to print

`N_to_print` an integer specifying the horizon how far to print the estimates and confidence intervals. The default is that all the values are printed (`N_to_print=N`).

Details

The model needs to be structural in order for this function to be applicable. A structural GMVAR model can be estimated by specifying the argument `structural_pars` in the function `fitGMVAR`.

The confidence bounds reflect uncertainty about the initial state (but currently not about the parameter estimates) if initial values are not specified. If initial values are specified, there won't currently be confidence intervals. See the cited paper by Virolainen (2020) for details about the algorithm.

Value

Returns a class `'girf'` list with the GIRFs in the first element (`$girf_res`) and the used arguments the rest. The first element containing the GIRFs is a list with the mth element containing the point estimates for the GIRF in `$point_est` (the first element) and confidence intervals in `$conf_ints` (the second element). The first row is for the GIRF at impact $(n = 0)$, the second for $n = 1$, the third for $n = 2$, and so on.

Methods (by generic)

- `plot`: plot method
- `print`: print method

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

`fitGMVAR`, `GMVAR`, `gmvar_to_sgmvar`, `reorder_W_columns`, `swap_W_signs`, `simulateGMVAR`, `predict.gmvar`, `profile_logliks`, `quantile_residual_tests`, `LR_test`, `Wald_test`

Examples

```
# These are long-running examples that use parallel computing.
data(eurusd, package="gmvarkit")
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(1.428, -0.808, 1.029, 5.84, 1.314, 0.145, 0.094, 1.292,
  -0.389, -0.07, -0.109, -0.281, 1.248, 0.077, -0.04, 1.266, -0.272,
  -0.074, 0.034, -0.313, 0.903, 0.718, -0.324, 2.079, 7, 1.44, 0.742)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
mod222s <- GMVAR(data, p=2, M=2, params=params222s, structural_pars=list(W=W_222))
mod222s
# Alternatively, use:
# fit222s <- fitGMVAR(data, p=2, M=2, structural_pars=list(W=W_222),
#                     ncalls=20, seeds=1:20)
# To obtain an estimated version of the same model.

# Estimating the GIRFs of both variables with default arguments
# (initial values are drawn from the stationary distribution of the process,
# 30 periods ahead, confidence levels 0.95 and 0.8):
girf1 <- GIRF(mod222s)
plot(girf1)
girf1

# Estimating the GIRF of the second variable only, 36 periods ahead
# and shock size 1, initial values drawn from the stationary distribution
# of the first regime, confidence level 0.9:
girf2 <- GIRF(mod222s, variables=2, shock_size=1, N=36, init_regimes=1, ci=0.9)
plot(girf2)

# Estimating the GIRFs of both variables, shock sizes 1 and 3, N=50 periods ahead,
# estimation based on 1000 Monte Carlo simulations, and fixed initial values given
```

```
# by the last p observations of the data:
girf3 <- GIRF(mod222s, shock_size=c(1, 3), N=50, R1=1000, init_values=mod222s$data)
```

GMVAR *Create a class 'gmvar' object defining a reduced form or structural GMVAR model*

Description

GMVAR creates a class 'gmvar' object that defines a reduced form or structural GMVAR model

Usage

```
GMVAR(
  data,
  p,
  M,
  d,
  params,
  conditional = TRUE,
  parametrization = c("intercept", "mean"),
  constraints = NULL,
  structural_pars = NULL,
  calc_cond_moments,
  calc_std_errors = FALSE
)

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

## S3 method for class 'gmvar'
residuals(object, ...)

## S3 method for class 'gmvar'
summary(object, ..., digits = 2)

## S3 method for class 'gmvar'
plot(x, ...)

## S3 method for class 'gmvar'
print(x, ..., digits = 2, summary_print = FALSE)
```

Arguments

data	a matrix or class 'ts' object with d>1 columns. Each column is taken to represent a single times series. NA values are not supported. Ignore if defining a model without data is desired.

`p` a positive integer specifying the autoregressive order of the model.

`M` a positive integer specifying the number of mixture components.

`d` number of times series in the system, i.e. `ncol(data)`. This can be used to define GMVAR models without data and can be ignored if `data` is provided.

`params` a real valued vector specifying the parameter values.

For unconstrained models: Should be size $((M(pd^2+d+d(d+1)/2+1)-1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p}))$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M)$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`conditional` a logical argument specifying whether the conditional or exact log-likelihood function should be used.

`parametrization`

`"mean"` or `"intercept"` determining whether the model is parametrized with regime means μ_m or intercept parameters $\phi_{m,0}$, m=1,...,M.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p}))(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'`

$(Mpd^2 xpd^2)$ where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

`calc_cond_moments`

should conditional means and covariance matrices should be calculated? Default is `TRUE` if the model contains data and `FALSE` otherwise.

`calc_std_errors`

should approximate standard errors be calculated?

`object` object of class `'gmvar'` generated by `fitGMVAR` or `GMVAR`.

`...` currectly not used.

`digits` number of digits to be printed.

`x` object of class `'gmvar'` generated by `fitGMVAR` or `GMVAR`.

`summary_print` if set to `TRUE` then the print will include log-likelihood and information criteria values.

Details

If data is provided, then also multivariate quantile residuals (*Kalliovirta and Saikkonen 2010*) are computed and included in the returned object.

The first plot displays the time series together with estimated mixing weights. The second plot displays (Gaussian) kernel density estimates of the individual series together with the marginal stationary density implied by the model. The colored regimewise stationary densities are multiplied with the mixing weight parameter estimates.

Value

Returns an object of class `'gmvar'` defining the specified reduced form or structural GMVAR model. Can be used to work with other functions provided in `gmvarkit`.

Remark that the first autocovariance/correlation matrix in `$uncond_moments` is for the lag zero, the second one for the lag one, etc.

Methods (by generic)

- `logLik`: Log-likelihood method
- `residuals`: residuals method to extract multivariate quantile residuals
- `summary`: summary method
- `plot`: plot method for class 'gmvar'
- `print`: print method

About S3 methods

Only the `print` method is available if data is not provided. If data is provided, then in addition to the ones listed above, the `predict` method is also available.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Kalliovirta L. and Saikkonen P. 2010. Reliable Residuals for Multivariate Nonlinear Time Series Models. *Unpublished Revision of HECER Discussion Paper No. 247*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

`fitGMVAR`, `add_data`, `swap_parametrization`, `GIRF`, `gmvar_to_sgmvar`, `reorder_W_columns`, `swap_W_signs`

Examples

```
# These examples use the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(1,2), d=2 model:
params122 <- c(0.623, -0.129, 0.959, 0.089, -0.006, 1.006, 1.746,
 0.804, 5.804, 3.245, 7.913, 0.952, -0.037, -0.019, 0.943, 6.926,
 3.982, 12.135, 0.789)
mod122 <- GMVAR(data, p=1, M=2, params=params122)
mod122

# GMVAR(1,2), d=2 model without data
mod122_2 <- GMVAR(p=1, M=2, d=2, params=params122)
mod122_2

# GMVAR(2,2), d=2 model with mean-parametrization:
params222 <- c(-11.904, 154.684, 1.314, 0.145, 0.094, 1.292, -0.389,
 -0.070, -0.109, -0.281, 0.920, -0.025, 4.839, 11.633, 124.983, 1.248,
  0.077, -0.040, 1.266, -0.272, -0.074, 0.034, -0.313, 5.855, 3.570,
  9.838, 0.740)
```

```
mod222 <- GMVAR(data, p=2, M=2, params=params222, parametrization="mean")
mod222

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(-11.964, 155.024, 11.636, 124.988, 1.314, 0.145, 0.094, 1.292,
 -0.389, -0.07, -0.109, -0.281, 1.248, 0.077, -0.04, 1.266, -0.272, -0.074,
  0.034, -0.313, 0.903, 0.718, -0.324, 2.079, 7.00, 1.44, 0.742)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
mod222s <- GMVAR(data, p=2, M=2, params=params222s, parametrization="mean",
 structural_pars=list(W=W_222))
mod222s

# GMVAR(2,2), d=2 model with AR-parameters restricted to be
# the same for both regimes:
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
params222c <- c(1.031, 2.356, 1.786, 3.000, 1.250, 0.060, 0.036,
 1.335, -0.290, -0.083, -0.047, -0.356, 0.934, -0.152, 5.201, 5.883,
 3.560, 9.799, 0.368)
mod222c <- GMVAR(data, p=2, M=2, params=params222c, constraints=C_mat)
mod222c

# GMVAR(2,2), d=2 model with AR-parameters restricted to be
# the same for both regimes and the non-diagonal elements of
# the coefficient matrices constrained to zero.
tmp <- matrix(c(1, rep(0, 10), 1, rep(0, 8), 1, rep(0, 10), 1),
 nrow=2*2^2, byrow=FALSE)
C_mat2 <- rbind(tmp, tmp)
params222c2 <- c(0.355, 3.193, -0.114, 2.829, 1.263, 1.338, -0.292,
 -0.362, 5.597, 3.456, 9.622, 0.982, -0.327, 5.236, 0.650)
mod222c2 <- GMVAR(data, p=2, M=2, params=params222c2,
  constraints=C_mat2)
mod222c2
```

`gmvarkit` *gmvarkit: Estimate Gaussian Mixture Vector Autoregressive (GMVAR) model*

Description

`gmvarkit` is a package for estimating Gaussian Mixture Vector Autoregressive (GMVAR) model. It provides functions for unconstrained and constraints maximum likelihood estimation of the model parameters, quantile residuals tests, graphical diagnostics, simulation from GMVAR processes, and forecasting.

Most of the functions documented are not exported but intended internal use only. The readme file is a good place to start, and the vignette might be useful too.

`gmvar_to_sgmvar` *Switch from two-regime reduced form GMVAR model to a structural GMVAR model.*

Description

`gmvar_to_sgmvar` constructs SGMVAR model based on a reduced form GMVAR model.

Usage

```
gmvar_to_sgmvar(gmvar)
```

Arguments

`gmvar`	an object of class `'gmvar'` created with `fitGMVAR` or `GMVAR`.

Details

The switch is made by simultaneously diagonalizing the two error term covariance matrices with a well known matrix decomposition (Muirhead, 1982, Theorem A9.9) and then normalizing the diagonal of the matrix W positive (which implies positive diagonal of the B-matrix). Models with more that two regimes are not supported because the matrix decomposition does not generally exists for more than two covariance matrices. If the model has only one regime (= regular SVAR model), a symmetric and pos. def. square root matrix of the error term covariance matrix is used.

The columns of W as well as the lambda parameters can be re-ordered (without changing the implied reduced form model) afterwards with the function `reorder_W_columns`. Also all signs in any column of W can be swapped (without changing the implied reduced form model) afterwards with the function `swap_W_signs`. These two functions work with models containing any number of regimes.

Value

Returns an object of class `'gmvar'` defining a structural GMVAR model based on a two-regime reduced form GMVAR model with the main diagonal of the B-matrix normalized to be positive.

References

- Muirhead R.J. 1982. Aspects of Multivariate Statistical Theory, *Wiley*.
- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

`fitGMVAR`, `GMVAR`, `GIRF`, `reorder_W_columns`, `swap_W_signs`

Examples

```
# These are long running examples
data(eurusd, package="gmvarkit")
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# Reduced form GMVAR(1,2) model
fit12 <- fitGMVAR(data, 1, 2, ncalls=1, seeds=3)

# Form a structural model based on the reduced form model:
mod12s <- gmvar_to_sgmvar(fit12)
```

---

in_paramspace *Determine whether the parameter vector lies in the parameter space*

Description

in_paramspace checks whether the given parameter vector lies in the parameter space. Does NOT consider the identifiability condition!

Usage

```
in_paramspace(p, M, d, params, constraints = NULL, structural_pars = NULL)
```

Arguments

p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
d	the number of time series in the system.
params	a real valued vector specifying the parameter values. **For unconstrained models:** Should be size $((M(pd^2+d+d(d+1)/2+1)-1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where • $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$ • ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$ • and $\sigma_m = vech(\Omega_m)$, m=1,...,M. **For constrained models:** Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where • ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix. **For structural GMVAR model:** Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where • $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ...,\lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ...,\phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

Returns `TRUE` if the given parameter vector lies in the parameter space and `FALSE` otherwise.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.

- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

Examples

```
# GMVAR(1,1), d=2 model:
params112 <- c(1.07, 127.71, 0.99, 0.00, -0.01, 0.99, 4.05,
  2.22, 8.87)
in_paramspace(p=1, M=1, d=2, params=params112)

# GMVAR(2,2), d=2 model:
params222 <- c(1.39, -0.77, 1.31, 0.14, 0.09, 1.29, -0.39,
 -0.07, -0.11, -0.28, 0.92, -0.03, 4.84, 1.01, 5.93, 1.25,
  0.08, -0.04, 1.27, -0.27, -0.07, 0.03, -0.31, 5.85, 3.57,
  9.84, 0.74)
in_paramspace(p=2, M=2, d=2, params=params222)

# GMVAR(2,2), d=2 model with AR-parameters restricted to be
# the same for both regimes:
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
params222c <- c(1.03, 2.36, 1.79, 3.00, 1.25, 0.06,0.04,
 1.34, -0.29, -0.08, -0.05, -0.36, 0.93, -0.15, 5.20,
 5.88, 3.56, 9.80, 0.37)
in_paramspace(p=2, M=2, d=2, params=params222c, constraints=C_mat)

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(1.03, 2.36, 1.79, 3, 1.25, 0.06, 0.04, 1.34, -0.29,
 -0.08, -0.05, -0.36, 1.2, 0.05, 0.05, 1.3, -0.3, -0.1, -0.05, -0.4,
  0.89, 0.72, -0.37, 2.16, 7.16, 1.3, 0.37)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
in_paramspace(p=2, M=2, d=2, params=params222s,
  structural_pars=list(W=W_222))
```

---

in_paramspace_int *Determine whether the parameter vector lies in the parameter space*

Description

in_paramspace_int checks whether the parameter vector lies in the parameter space.

Usage

```
in_paramspace_int(
  p,
  M,
  d,
  params,
  all_boldA,
  alphas,
```

```
  all_Omega,
  W_constraints = NULL
)
```

Arguments

p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
d	the number of time series in the system.
params	a real valued vector specifying the parameter values. **For reduced form model:** Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where: • $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$ • ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$ • and $\sigma_m = vech(\Omega_m)$, m=1,...,M. **For structural GMVAR model:** Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where • $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component. Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the i:th coefficient matrix of the m:th mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with the regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by KMS (2016) introducing the GMVAR model.
all_boldA	3D array containing the $((dp)x(dp))$ "bold A" matrices related to each mixture component VAR-process, obtained from `form_boldA`. Will be computed if not given.
alphas	(Mx1) vector containing all mixing weight parameters, obtained from `pick_alphas`.
all_Omega	3D array containing all covariance matrices Ω_m, obtained from `pick_Omegas`.
W_constraints	set `NULL` for reduced form models. For structural models, this should be the constraint matrix W from the list of structural parameters.

Details

The parameter vector in the argument `params` should be unconstrained and it is used for structural models only.

Value

Returns `TRUE` if the given parameter values are in the parameter space and `FALSE` otherwise. This function does NOT consider the identifiability condition!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`is_stationary` *Check the stationary condition of a given GMVAR model*

Description

`is_stationary` checks the stationarity condition of a GMVAR model.

Usage

```
is_stationary(
  p,
  M,
  d,
  params,
  all_boldA = NULL,
  structural_pars = NULL,
  tolerance = 0.001
)
```

Arguments

`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`d`	the number of time series in the system.
`params`	a real valued vector specifying the parameter values.

For reduced form model: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where:

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For structural GMVAR model: Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the i:th coefficient matrix of the m:th mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W

and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped.

If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with the regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by KMS (2016) introducing the GMVAR model.

`all_boldA` 3D array containing the $((dp)x(dp))$ "bold A" matrices related to each mixture component VAR-process, obtained from `form_boldA`. Will be computed if not given.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

`tolerance` Returns `FALSE` if modulus of any eigenvalue is larger or equal to `1-tolerance`.

Details

If the model is constrained, remove the constraints first with the function `reform_constrained_pars`.

Value

Returns `TRUE` if the model is stationary and `FALSE` if not. Based on the argument `tolerance`, `is_stationary` may return `FALSE` when the parameter vector is in the stationarity region, but very close to the boundary (this is used to ensure numerical stability in estimation of the model parameters).

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.

- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`iterate_more` *Maximum likelihood estimation of a GMVAR model with preliminary estimates*

Description

`iterate_more` uses a variable metric algorithm to finalize maximum likelihood estimation of a GMVAR model (object of class `'gmvar'`) which already has preliminary estimates.

Usage

```
iterate_more(gmvar, maxit = 100, calc_std_errors = TRUE)
```

Arguments

`gmvar`	an object of class `'gmvar'` created with `fitGMVAR` or `GMVAR`.
`maxit`	the maximum number of iterations in the variable metric algorithm.
`calc_std_errors`	should approximate standard errors be calculated?

Details

The purpose of `iterate_more` is to provide a simple and convenient tool to finalize the estimation when the maximum number of iterations is reached when estimating a GMVAR model with the main estimation function `fitGMVAR`. `iterate_more` is essentially a wrapper around the function `optim` from the package `stats` and `GMVAR` from the package `gmvarkit`.

Value

Returns an object of class `'gmvar'` defining the estimated GMVAR model.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Kalliovirta L. and Saikkonen P. 2010. Reliable Residuals for Multivariate Nonlinear Time Series Models. *Unpublished Revision of HECER Discussion Paper No. 247*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

`fitGMVAR`, `GMVAR`, `optim`, `profile_logliks`

Examples

```
## These are long running examples that use parallel computing!

# These examples use the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(1,2) model, only 5 iterations of the variable metric
# algorithm
fit12 <- fitGMVAR(data, p=1, M=2, maxit=5)
fit12

# Iterate more:
fit12_2 <- iterate_more(fit12)
fit12_2

# Structural GMVAR(1,2) model identified with sign
# constraints. Only 10 iterations of the variable metric
# algorithm
W_122 <- matrix(c(1, -1, NA, 1), nrow=2)
fit12s <- fitGMVAR(data, p=1, M=2, structural_pars=list(W=W_122),
  ncalls=10, maxit=10, seeds=1:10)
fit12s

# Iterate more:
fit12s_2 <- iterate_more(fit12s)
fit12s_2

# GMVAR(2,2) model with autoregressive parameters restricted
# to be the same for all regimes, only 10 iterations of the
# variable metric algorithm
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
fit22c <- fitGMVAR(data, p=2, M=2, constraints=C_mat, maxit=10)
fit22c

# Iterate more:
fit22c_2 <- iterate_more(fit22c)
fit22c_2

# GMVAR(3,2) model, only 10 iterations of the variable metric
# algorithm
fit32 <- fitGMVAR(data, p=3, M=2, maxit=10)
fit32

# Iterate more:
fit32_2 <- iterate_more(fit32)
fit32_2
```

`loglikelihood` *Compute log-likelihood of a GMVAR model using parameter vector*

Description

`loglikelihood` computes log-likelihood of a GMVAR model using parameter vector instead of an object of class 'gmvar'. Exists for convenience if one wants to for example employ other estimation algorithms than the ones used in `fitGMVAR`. Use `minval` to control what happens when the parameter vector is outside the parameter space.

Usage

```
loglikelihood(
  data,
  p,
  M,
  params,
  conditional = TRUE,
  parametrization = c("intercept", "mean"),
  constraints = NULL,
  structural_pars = NULL,
  minval = NA
)
```

Arguments

`data`	a matrix or class `'ts'` object with `d>1` columns. Each column is taken to represent a single time series. `NA` values are not supported.
`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`params`	a real valued vector specifying the parameter values.

For unconstrained models: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ...,\lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`conditional` a logical argument specifying whether the conditional or exact log-likelihood function should be used.

`parametrization`

`"mean"` or `"intercept"` determining whether the model is parametrized with regime means μ_m or intercept parameters $\phi_{m,0}$, m=1,...,M.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ...,\phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

`minval` the value that will be returned if the parameter vector does not lie in the parameter space (excluding the identification condition).

Details

loglikelihood_int takes use of the function dmvn from the package mvnfast to cut down computation time. Values extremely close to zero are handled with the package Brobdingnag.

Value

Returns log-likelihood if params is in the parameters space and minval if not.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

fitGMVAR, GMVAR, calc_gradient

Examples

```
data <- cbind(10*eurusd[,1], 100*eurusd[,2])

# GMVAR(2, 2), d=2 model;
params222 <- c(-11.904, 154.684, 1.314, 0.145, 0.094, 1.292, -0.389,
 -0.070, -0.109, -0.281, 0.920, -0.025, 4.839, 11.633, 124.983, 1.248,
  0.077, -0.040, 1.266, -0.272, -0.074, 0.034, -0.313, 5.855, 3.570,
  9.838, 0.740)
loglikelihood(data=data, p=2, M=2, params=params222, parametrization="mean")

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(1.03, 2.36, 1.79, 3, 1.25, 0.06, 0.04, 1.34, -0.29,
 -0.08, -0.05, -0.36, 1.2, 0.05, 0.05, 1.3, -0.3, -0.1, -0.05, -0.4,
  0.89, 0.72, -0.37, 2.16, 7.16, 1.3, 0.37)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
loglikelihood(data=data, p=2, M=2, params=params222s, structural_pars=list(W=W_222))
```

---

loglikelihood_int *Compute log-likelihood of a Gaussian mixture vector autoregressive model*

Description

loglikelihood_int computes log-likelihood of a GMVAR model.

Usage

```
loglikelihood_int(
  data,
  p,
  M,
  params,
  conditional = TRUE,
  parametrization = c("intercept", "mean"),
  constraints = NULL,
  structural_pars = NULL,
 to_return = c("loglik", "mw", "mw_tplus1", "loglik_and_mw", "terms", "regime_cmeans",
    "total_cmeans", "total_ccovs"),
  check_params = TRUE,
  minval = NULL
)
```

Arguments

data	a matrix or class 'ts' object with d>1 columns. Each column is taken to represent a single time series. NA values are not supported.
p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
params	a real valued vector specifying the parameter values.

For unconstrained models: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d + d(d+1)/2 + 1) + q - 1)x1)$ and have form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter.

The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`conditional` a logical argument specifying whether the conditional or exact log-likelihood function should be used.

`parametrization`

`"mean"` or `"intercept"` determining whether the model is parametrized with regime means μ_m or intercept parameters $\phi_{m,0}$, m=1,...,M.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

`to_return` should the returned object be the log-likelihood value, mixing weights, mixing weights including value for $alpha_{m,T+1}$, a list containing log-likelihood value and mixing weights, or the terms $l_t : t = 1, .., T$ in the log-likelihood function (see *KMS 2016, eq.(9)*)? Or should the regimewise conditional means, total conditional means, or total conditional covariance matrices be returned? Default is the log-likelihood value (`"loglik"`).

`check_params` should it be checked that the parameter vector satisfies the model assumptions? Can be skipped to save computation time if it does for sure.

`minval` the value that will be returned if the parameter vector does not lie in the parameter space (excluding the identification condition).

Details

loglikelihood_int takes use of the function dmvn from the package mvnfast to cut down computation time. Values extremely close to zero are handled with the package Brobdingnag.

Value

By default: log-likelihood value of the specified GMVAR model,

If to_return=="mw"**:** a size ((n_obs-p)xM) matrix containing the mixing weights: for m:th component in m:th column.

If to_return=="mw_tplus1"**:** a size ((n_obs-p+1)xM) matrix containing the mixing weights: for m:th component in m:th column. The last row is for $\alpha_{m,T+1}$.

If to_return=="terms"**:** a size ((n_obs-p)x1) numeric vector containing the terms l_t.

if to_return=="loglik_and_mw"**:** a list of two elements. The first element contains the log-likelihood value and the second element contains the mixing weights.

If to_return=="regime_cmeans"**:** an [T-p,d,M] array containing the regimewise conditional means (the first p values are used as the initial values).

If to_return=="total_cmeans"**:** a [T-p,d] matrix containing the conditional means of the process (the first p values are used as the initial values).

If to_return=="total_ccov"**:** an [d,d,T-p] array containing the conditional covariance matrices of the process (the first p values are used as the initial values).

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

LR_test *Perform likelihood ratio test for a GMVAR or SGMVAR model*

Description

LR_test performs a likelihood ratio test for a GMVAR or SGMVAR model

Usage

```
LR_test(gmvar1, gmvar2)

## S3 method for class 'lr'
print(x, ..., digits = 4)
```

Arguments

gmvar1	an object of class 'gmvar' generated by fitGMVAR or GMVAR, containing the **freely estimated** model.
gmvar2	an object of class 'gmvar' generated by fitGMVAR or GMVAR, containing the **constrained** model.
x	object of class 'lr' generated by the function LR_test.
...	currently not used.
digits	how many significant digits to print?

Details

Performs a likelihood ratio test, testing the null hypothesis that the true parameter value lies in the constrained parameter space. Under the null, the test statistic is asymptotically χ^2-distributed with k degrees of freedom, k being the difference in the dimensions of the unconstrained and constrained parameter spaces.

Note that this function does **not** verify that the two models are actually nested.

Value

Returns an object of class $'lr'$ containing the test statistic and the related p-value.

Methods (by generic)

- print: print method

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

Wald_test, fitGMVAR, GMVAR, diagnostic_plot, profile_logliks, quantile_residual_tests, cond_moment_plot

Examples

```
# Load the data
data(eurusd, package="gmvarkit")
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
fit222s <- fitGMVAR(data, p=2, M=2, structural_pars=list(W=W_222),
```

```
                    ncalls=1, seeds=1)

# The same model but the AR coefficients restricted to be the same
# in both regimes:
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
fit222sc <- fitGMVAR(data, p=2, M=2, constraints=C_mat,
                     structural_pars=list(W=W_222),
                     ncalls=1, seeds=1)

# Test whether the constraints are supported by the data:
LR_test(fit222s, fit222sc)
```

`n_params` *Calculate the number of parameters in GMVAR model parameter vector*

Description

`n_params` calculates the number of parameters in the model.

Usage

```
n_params(p, M, d, constraints = NULL, structural_pars = NULL)
```

Arguments

`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`d`	the number of time series in the system.
`constraints`	a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ...,\phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.
`structural_pars`	If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements: • `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.

- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

Returns the number of parameters in parameter vector of the specified GMVAR model.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`pick_allA` *Pick coefficient all matrices*

Description

`pick_allA` picks all coefficient matrices $A_{m,i}(i = 1, .., p, m = 1, .., M)$ from the given parameter vector so that they are arranged in a 4D array with the fourth dimension indicating each component and third dimension indicating each lag.

Usage

```
pick_allA(p, M, d, params, structural_pars = NULL)
```

Arguments

`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`d`	the number of time series in the system.
`params`	a real valued vector specifying the parameter values.

For reduced form model: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where:

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$

- ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For structural GMVAR model: Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M)$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the i:th coefficient matrix of the m:th mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped.

If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with the regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by KMS (2016) introducing the GMVAR model.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

Returns a 4D array containing the coefficient matrices of the all components. Coefficient matrix $A_{m,i}$ can be obtained by choosing `[,,i,m]`.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.

- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`pick_all_phi0_A` *Pick all $\phi\_m, 0$ or μ_m and $A\_m, 1, ..., A\_m, p$ parameter values*

Description

`pick_all_phi0_A` picks the intercept or mean parameters and vectorized coefficient matrices from the given parameter vector.

Usage

```
pick_all_phi0_A(p, M, d, params, structural_pars = NULL)
```

Arguments

`p` a positive integer specifying the autoregressive order of the model.

`M` a positive integer specifying the number of mixture components.

`d` the number of time series in the system.

`params` a real valued vector specifying the parameter values.

For reduced form model: Should be size $((M(pd^2 + d + d(d + 1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where:

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For structural GMVAR model: Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the i:th coefficient matrix of the m:th mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped.

If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with the regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by KMS (2016) introducing the GMVAR model.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

Returns a $((pd^2 + d)xM)$ matrix containing $(\phi_{m,0}, vec(A_{m,1}), ..., vec(A_{m,p}))$ in the m:th column, or $(\mu_m, vec(A_{m,1}), ..., vec(A_{m,p}))$ if the parameter vector is mean-parametrized, m=1,..,M.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`pick_alphas` *Pick mixing weight parameters* $\alpha\_m, m = 1, ..., M$

Description

`pick_alphas` picks the mixing weight parameters from the given parameter vector.

Usage

```
pick_alphas(p, M, d, params)
```

Arguments

p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
d	the number of time series in the system.
params	a real valued vector specifying the parameter values.

For reduced form model: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where:

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p}))$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For structural GMVAR model: Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the i:th coefficient matrix of the m:th mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped.

If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with the regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by KMS (2016) introducing the GMVAR model.

Value

Returns a length M vector containing the mixing weight parameters $alpha_m, m = 1, ..., M$, including non-parametrized $alpha_M$.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

pick_Am *Pick coefficient matrices*

Description

pick_Am picks the coefficient matrices $A_{m,i}(i = 1, .., p)$ from the given parameter vector so that they are arranged in a 3D array with the third dimension indicating each lag.

Usage

```
pick_Am(p, M, d, params, m, structural_pars = NULL)
```

Arguments

p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
d	number of time series in the system, i.e. the dimension.
params	a real valued vector specifying the parameter values. **For unconstrained models:** Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where • $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$ • ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$ • and $\sigma_m = vech(\Omega_m)$, m=1,...,M. **For constrained models:** Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where • ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix. **For structural GMVAR model:** Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where • $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component. **If AR parameters are constrained:** Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above. **If W is constrained:** Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints. **If λ_{mi} are constrained:** Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix. Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If parametrization=="mean", just replace each $\phi_{m,0}$ with regimewise mean μ_m.

$vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`m` which component?

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

Returns a 3D array containing the coefficient matrices of the given component. A coefficient matrix $A_{m,i}$ can be obtained by choosing `[,,i]`.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`pick_Ami` *Pick coefficient matrix*

Description

`pick_Ami` picks the coefficient matrix $A_{m,i}$ from the given parameter vector.

Usage

```
pick_Ami(p, M, d, params, m, i, structural_pars = NULL, unvec = TRUE)
```

Arguments

p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
d	number of time series in the system, i.e. the dimension.
params	a real valued vector specifying the parameter values. **For unconstrained models:** Should be size $((M(pd^2+d+d(d+1)/2+1)-1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where • $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$ • ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$ • and $\sigma_m = vech(\Omega_m)$, m=1,...,M. **For constrained models:** Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where • ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix. **For structural GMVAR model:** Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where • $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component. **If AR parameters are constrained:** Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above. **If W is constrained:** Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints. **If λ_{mi} are constrained:** Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix. Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.
m	which component?
i	which lag in 1,...,p?
structural_pars	If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

`unvec` if `FALSE` then vectorized version of $A_{m,i}$ will be returned instead of matrix. Default if `TRUE`.

Details

Does not support constrained parameter vectors.

Value

Returns the i:th lag coefficient matrix of m:th component, $A_{m,i}$.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`pick_lambdas` *Pick the structural parameters eigenvalue 'lambdas'*

Description

`pick_lambdas` picks the structural parameters eigenvalue 'lambdas from a parameter vector

Usage

```
pick_lambdas(p, M, d, params, structural_pars = NULL)
```

Arguments

`p` a positive integer specifying the autoregressive order of the model.

`M` a positive integer specifying the number of mixture components.

`d` the number of time series in the system.

`params` a real valued vector specifying the parameter values.

For reduced form model: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where:

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For structural GMVAR model: Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the i:th coefficient matrix of the m:th mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped.

If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with the regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by KMS (2016) introducing the GMVAR model.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Details

Constrained parameter vectors are not supported. Not even constraints in W!

Value

Returns a length $(d * (M-1))$ vector $(\lambda_2, ..., \lambda_M)$ (see the argument `params`) from a parameter vector of a SGMVAR model. Returns `numeric(0)` for reduced form models or when $M = 1$.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`pick_Omegas` *Pick covariance matrices*

Description

`pick_Omegas` picks the covariance matrices $\Omega_m (m = 1, .., M)$ from the given parameter vector so that they are arranged in a 3D array with the third dimension indicating each component.

Usage

```
pick_Omegas(p, M, d, params, structural_pars = NULL)
```

Arguments

`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`d`	the number of time series in the system.
`params`	a real valued vector specifying the parameter values.

For reduced form model: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where:

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For structural GMVAR model: Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the i:th coefficient matrix of the m:th mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped.

If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with the regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by KMS (2016) introducing the GMVAR model.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

Returns a 3D array containing the covariance matrices of the given model. Coefficient matrix Ω_m can be obtained by choosing `[,,m]`.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

pick_phi0 *Pick $\phi\_m, 0$ or μ_m, m=1,..,M vectors*

Description

pick_phi0 picks the intercept or mean parameters from the given parameter vector.

Usage

```
pick_phi0(p, M, d, params, structural_pars = NULL)
```

Arguments

p — a positive integer specifying the autoregressive order of the model.

M — a positive integer specifying the number of mixture components.

d — the number of time series in the system.

params — a real valued vector specifying the parameter values.

For reduced form model: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where:

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For structural GMVAR model: Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the i:th coefficient matrix of the m:th mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped.

If parametrization=="mean", just replace each $\phi_{m,0}$ with the regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by KMS (2016) introducing the GMVAR model.

structural_pars

If NULL a reduced form model is considered. For structural model, should be a list containing the following elements:

- W - a (dxd) matrix with its entries imposing constraints on W: NA indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.

- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

Returns a (dxM) matrix containing $\phi_{m,0}$ in the m:th column or μ_m if the parameter vector is mean-parametrized, , $m = 1, .., M$.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`pick_regime` *Pick regime parameters* $\upsilon\_m = (\phi\_m, 0, \phi\_m, \sigma\_m)$

Description

`pick_regime` picks the regime-parameters from the given parameter vector.

Usage

```
pick_regime(p, M, d, params, m, structural_pars = NULL)
```

Arguments

`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`d`	number of time series in the system, i.e. the dimension.
`params`	a real valued vector specifying the parameter values. **For unconstrained models:** Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M)$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`m` which component?

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Details

Models with AR or lambda parameter constraints are currently not supported.

Value

For reduced form models: returns length $pd^2+d+d(d+1)/2$ vector containing $\upsilon_m = (\phi_{m,0},\phi_m,\sigma_m)$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,1})$ and $\sigma_m = vech(\Omega_m)$.

For structural models: returns the length $pd^2 + d$ vector $(\phi_{m,0},\phi_m)$.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

---

pick_W *Pick the structural parameter matrix W*

Description

`pick_W` picks the structural parameter matrix W from a parameter vector

Usage

```
pick_W(p, M, d, params, structural_pars = NULL)
```

Arguments

`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`d`	the number of time series in the system.
`params`	a real valued vector specifying the parameter values. **For reduced form model:** Should be size $((M(pd^2 + d + d(d + 1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where: • $\upsilon_m = (\phi_{m,0},\phi_m,\sigma_m)$ • $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})$ • and $\sigma_m = vech(\Omega_m)$, m=1,...,M. **For structural GMVAR model:** Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0},\phi_1, ...,\phi_M, vec(W),\lambda_2, ...,\lambda_M$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the i:th coefficient matrix of the m:th mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped.

If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with the regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by KMS (2016) introducing the GMVAR model.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Details

Constrained parameter vectors are not supported. Not even constraints in W!

Value

Returns a (dxd) matrix W from a parameter vector of a SGMVAR model. Returns `NULL` for reduced form models.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

plot.gmvarpred *plot method for class 'gmvarpred' objects*

Description

plot.gmvarpred is plot method for gmvarpred objects.

Usage

```
## S3 method for class 'gmvarpred'
plot(x, ..., nt, mix_weights = TRUE, add_grid = TRUE)
```

Arguments

x	object of class 'gmvarpred' generated by predict.gmvar.
...	arguments passed to grid which plots grid to the figure.
nt	a positive integer specifying the number of observations to be plotted along with the prediction (ignored if plot_res==FALSE). Default is round(nrow(data)*0.15).
mix_weights	TRUE if forecasts for mixing weights should be plotted, FALSE in not.
add_grid	should grid be added to the plots?

Details

This method is used plot forecasts of GMVAR processes

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

plot.qrtest *Quantile residual tests*

Description

quantile_residual_tests performs quantile residual tests described by *Kalliovirta and Saikkonen 2010*, testing autocorrelation, conditional heteroskedasticity, and normality.

Usage

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

## S3 method for class 'qrtest'
print(x, ..., digits = 3)

quantile_residual_tests(
  gmvar,
  lags_ac = c(1:2, 4, 8),
  lags_ch = lags_ac,
  nsimu = 1,
  print_res = TRUE
)
```

Arguments

x	object of class 'qrtest' generated by the function quantile_residual_tests).
...	currently not used.
digits	the number of decimals to print
gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.
lags_ac	a positive integer vector specifying the lags used to test autocorrelation.
lags_ch	a positive integer vector specifying the lags used to test conditional heteroskedasticity.
nsimu	to how many simulations should the covariance matrix Omega used in the qr-tests be based on? If smaller than sample size, then the covariance matrix will be evaluated from the sample. Larger number of simulations might improve the tests size properties but increase the computation time.
print_res	should the test results be printed while computing the tests?

Value

Returns an object of class 'qrtest' which has its own print method. The returned object is a list containing the quantile residual test results for normality, autocorrelation, and conditional heteroskedasticity. The autocorrelation and conditional heteroskedasticity results also contain the associated (vectorized) individual statistics divided by their standard errors (see *Kalliovirta and Saikkonen 2010*, s.17-20) under the label $ind_stats.

Methods (by generic)

- plot: Plot p-values of the autocorrelation and conditional heteroskedasticity tests.
- print: Print method for class 'qrtest'

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Kalliovirta L. and Saikkonen P. 2010. Reliable Residuals for Multivariate Nonlinear Time Series Models. *Unpublished Revision of HECER Discussion Paper No. 247*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

fitGMVAR, GMVAR, quantile_residuals, GIRF, diagnostic_plot, predict.gmvar, profile_logliks, LR_test, Wald_test, cond_moment_plot

Examples

```
## These are long running examples that use parallel computing!

# These examples use the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(1,2) model with default settings
fit12 <- fitGMVAR(data, p=1, M=2)
qrtests12 <- quantile_residual_tests(fit12)
qrtests12
plot(qrtests12)

# Structural GMVAR(1,2) model identified with sign
# constraints. The sign constraints (which fully identify
# the shocks) are in line with the reduced form model,
# so the test results are the same.
W_122 <- matrix(c(1, NA, -1, 1), nrow=2)
fit12s <- fitGMVAR(data, p=1, M=2, structural_pars=list(W=W_122),
  ncalls=10, seeds=1:10)
qrtests12s <- quantile_residual_tests(fit12s)
qrtests12s

# GMVAR(2,2) model with mean parametrization
fit22 <- fitGMVAR(data, p=2, M=2, parametrization="mean",
  ncalls=1, seeds=20)
qrtests22 <- quantile_residual_tests(fit22)
qrtests22

# GMVAR(2,2) model with autoregressive parameters restricted
# to be the same for all regimes
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
fit22c <- fitGMVAR(data, p=2, M=2, constraints=C_mat, ncalls=12)
qrtests22c <- quantile_residual_tests(fit22c, lags_ac=c(1, 4),
                nsimu=10000, print_res=TRUE)
```

```
qrtests22c
```

`predict.gmvar` *Predict method for class 'gmvar' objects*

Description

Forecast GMVAR process defined as a class `'gmvar'` object. The forecasts are computed by performing independent simulations and using the sample medians or means as point forecasts and empirical quantiles as prediction intervals. For one-step-ahead predictions using the exact conditional mean is also supported.

Usage

```
## S3 method for class 'gmvar'
predict(
  object,
  ...,
  n_ahead,
  n_simu = 2000,
  pi = c(0.95, 0.8),
  pi_type = c("two-sided", "upper", "lower", "none"),
  pred_type = c("median", "mean", "cond_mean"),
  plot_res = TRUE,
  mix_weights = TRUE,
  nt
)
```

Arguments

`object`	an object of class `'gmvar'`, generated by function `fitGMVAR` or `GMVAR`.
`...`	additional arguments passed to `grid` (ignored if `plot_res==FALSE`) which plots grid to the figure.
`n_ahead`	how many steps ahead should be predicted?
`n_simu`	to how many independent simulations should the forecast be based on?
`pi`	a numeric vector specifying the confidence levels of the prediction intervals.
`pi_type`	should the prediction intervals be "two-sided", "upper", or "lower"?
`pred_type`	should the prediction be based on sample "median" or "mean"? Or should it be one-step-ahead forecast based on the exact conditional mean (`"cond_mean"`)? Prediction intervals won't be calculated if the exact conditional mean is used.
`plot_res`	should the results be plotted?
`mix_weights`	`TRUE` if forecasts for mixing weights should be plotted, `FALSE` in not.
`nt`	a positive integer specifying the number of observations to be plotted along with the prediction (ignored if `plot_res==FALSE`). Default is `round(nrow(data)*0.15)`.

Value

Returns a class 'gmvarpred' object containing, among the specifications,...

$pred Point forecasts

$pred_int Prediction intervals, as [,,d].

$mix_pred Point forecasts for the mixing weights

mix_pred_int Individual prediction intervals for mixing weights, as [,,m], m=1,..,M.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

GIRF

Examples

```
## These are long running examples that use parallel computing!

# These examples use the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(2,2) model
fit22 <- fitGMVAR(data, p=2, M=2, ncalls=12, seeds=42:53)
p1 <- predict(fit22, n_ahead=20, pred_type="median")
p1
p2 <- predict(fit22, n_ahead=10, nt=20, lty=1)
p2
p3 <- predict(fit22, n_ahead=10, pi=c(0.99, 0.90, 0.80, 0.70),
              nt=30, lty=0)
p3

# GMVAR(1,2) model
fit12 <- fitGMVAR(data, p=1, M=2)
p1 <- predict(fit12, n_ahead=1, pred_type="cond_mean",
              plot_res=FALSE)
p1
p2 <- predict(fit12, n_ahead=10, pred_type="mean")
p2
p3 <- predict(fit12, n_ahead=10, pi_type="upper")
p3

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
```

```
params222s <- c(-11.964, 155.024, 11.636, 124.988, 1.314, 0.145, 0.094, 1.292,
 -0.389, -0.07, -0.109, -0.281, 1.248, 0.077, -0.04, 1.266, -0.272, -0.074,
  0.034, -0.313, 0.903, 0.718, -0.324, 2.079, 7.00, 1.44, 0.742)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
mod222s <- GMVAR(data, p=2, M=2, params=params222s, parametrization="mean",
 structural_pars=list(W=W_222))
p1 <- predict(mod222s, n_ahead=10)
```

`print.gmvarpred` *Print method for class 'gmvarpred' objects*

Description

`print.gmvarpred` is a print method for object generated by `predict.gmvar`.

Usage

```
## S3 method for class 'gmvarpred'
print(x, ..., digits = 2)
```

Arguments

`x`	object of class `'gmvarpred'` generated by `predict.gmvar`.
`...`	currently not used.
`digits`	the number of decimals to print

Examples

```
# This example uses the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(2,2), d=2 model
params222 <- c(-11.904, 154.684, 1.314, 0.145, 0.094, 1.292, -0.389,
 -0.070, -0.109, -0.281, 0.920, -0.025, 4.839, 11.633, 124.983, 1.248,
  0.077, -0.040, 1.266, -0.272, -0.074, 0.034, -0.313, 5.855, 3.570,
  9.838, 0.740)
mod222 <- GMVAR(data, p=2, M=2, params=params222, parametrization="mean")
pred222 <- predict(mod222, n_ahead=3, plot_res=FALSE)
print(pred222)
print(pred222, digits=3)
```

print.gmvarsum *Summary print method from objects of class 'gmvarsum'*

Description

print.gmvarsum is a print method for object 'gmvarsum' generated by summary.gmvar.

Usage

```
## S3 method for class 'gmvarsum'
print(x, ..., digits)
```

Arguments

x	object of class 'gmvarsum' generated by summary.gmvar.
...	currently not used.
digits	the number of digits to be printed.

Examples

```
# This example uses the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(2,2), d=2 model
params222 <- c(-11.904, 154.684, 1.314, 0.145, 0.094, 1.292, -0.389,
 -0.070, -0.109, -0.281, 0.920, -0.025, 4.839, 11.633, 124.983, 1.248,
  0.077, -0.040, 1.266, -0.272, -0.074, 0.034, -0.313, 5.855, 3.570,
  9.838, 0.740)
mod222 <- GMVAR(data, p=2, M=2, params=params222, parametrization="mean")
sumry222 <- summary(mod222)
print(sumry222)
```

print_std_errors *Print standard errors of GMVAR model in the same form as the model estimates are printed*

Description

print_std_errors prints the approximate standard errors of GMVAR model in the same form as the parameters of objects of class 'gmvar' are printed.

Usage

```
print_std_errors(gmvar, digits = 3)
```

Arguments

gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.
digits	how many digits should be printed?

Details

The main purpose of print_std_errors is to provide a convenient tool to match the standard errors to certain parameter estimates.

Note that if linear constraints are imposed and they involve summations or multiplications, then the AR parameter standard errors are printed separately as they don't correspond one-to-one to the model parameter standard errors.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Kalliovirta L. and Saikkonen P. 2010. Reliable Residuals for Multivariate Nonlinear Time Series Models. *Unpublished Revision of HECER Discussion Paper No. 247*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

profile_logliks, fitGMVAR, GMVAR, print.gmvar, swap_parametrization

Examples

```
## These are long running examples that use parallel computing!

# These examples use the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(1,2) model with default settings
fit12 <- fitGMVAR(data, p=1, M=2)
fit12
print_std_errors(fit12)

# GMVAR(2,2) model with mean parametrization
fit22 <- fitGMVAR(data, p=2, M=2, parametrization="mean")
fit22
print_std_errors(fit22)

# GMVAR(2,2) model with autoregressive parameters restricted
# to be the same for all regimes
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
fit22c <- fitGMVAR(data, p=2, M=2, constraints=C_mat)
```

```
fit22c
print_std_errors(fit22c)

# GMVAR(2,2) model with autoregressive parameters restricted
# to be the same for all regimes and non-diagonl elements
# the coefficient matrices constrained to zero.
tmp <- matrix(c(1, rep(0, 10), 1, rep(0, 8), 1, rep(0, 10), 1),
 nrow=2*2^2, byrow=FALSE)
C_mat2 <- rbind(tmp, tmp)
fit22c2 <- fitGMVAR(data, p=2, M=2, constraints=C_mat2, ncalls=10)
fit22c2
print_std_errors(fit22c2)
```

`profile_logliks` *Plot profile log-likehoods around the estimates*

Description

`profile_logliks` plots profile log-likelihoods around the estimates.

Usage

```
profile_logliks(
  gmvar,
  which_pars,
  scale = 0.02,
  nrows,
  ncols,
  precission = 200
)
```

Arguments

`gmvar`	an object of class `'gmvar'` created with `fitGMVAR` or `GMVAR`.
`which_pars`	the profile log-likelihood function of which parameters should be plotted? An integer vector specifying the positions of the parameters in the parameter vector. The parameter vector has the form...

For unconstrained models: Should be size $((M(pd^2+d+d(d+1)/2+1)-1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where:

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where:

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$. Here C is (Mpd^2xq) constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the i:th coefficient matrix of the m:th mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter.

The default is that profile log-likelihood functions for all parameters are plotted.

`scale` a numeric scalar specifying the interval plotted for each estimate: the estimate plus-minus `abs(scale*estimate)`.

`nrows` how many rows should be in the plot-matrix? The default is `max(ceiling(log2(length(which_pars))-1),1)`.

`ncols` how many columns should be in the plot-matrix? The default is `ceiling(length(which_pars)/nrows)`. Note that `nrows*ncols` should not be smaller than the length of `which_pars`.

`precission` at how many points should each profile log-likelihood be evaluated at?

Details

When the number of parameters is large, it might be better to plot a smaller number of profile log-likelihood functions at a time using the argument `which_pars`.

The red vertical line points the estimate.

Value

Only plots to a graphical device and doesn't return anything.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

`get_soc`, `diagnostic_plot`, `fitGMVAR`, `GMVAR`, `GIRF`, `LR_test`, `Wald_test`, `cond_moment_plot`

Examples

```
# These examples use the data 'eurusd' which comes with the
# package, but in a scaled form (similar to Kalliovirta et al. 2016).
data(eurusd, package="gmvarkit")
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(1,2) model: 10 estimation rounds with seeds set
# for reproducibility
fit12 <- fitGMVAR(data, p=1, M=2, ncalls=10, seeds=1:10)
fit12
profile_logliks(fit12)
```

```
# Structural GMVAR(1,2) model identified with sign
# constraints.
W_122 <- matrix(c(1, -1, NA, 1), nrow=2)
fit12s <- fitGMVAR(data, p=1, M=2, structural_pars=list(W=W_122),
  ncalls=10, seeds=1:10)
profile_logliks(fit12s)

# GMVAR(2,2) model with mean parametrization
fit22 <- fitGMVAR(data, p=2, M=2, parametrization="mean",
                  ncalls=16, seeds=11:26)
profile_logliks(fit22)

# GMVAR(2,2) model with autoregressive parameters restricted
# to be the same for both regimes
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
fit22c <- fitGMVAR(data, p=2, M=2, constraints=C_mat)
profile_logliks(fit22c)

# GMVAR(2,2) model with autoregressive parameters restricted
# to be the same for both regimes and non-diagonl elements
# the coefficient matrices constrained to zero.
tmp <- matrix(c(1, rep(0, 10), 1, rep(0, 8), 1, rep(0, 10), 1),
 nrow=2*2^2, byrow=FALSE)
C_mat2 <- rbind(tmp, tmp)
fit22c2 <- fitGMVAR(data, p=2, M=2, constraints=C_mat2)
profile_logliks(fit22c2)
```

`quantile_residuals` *Calculate multivariate quantile residuals of a GMVAR model*

Description

`quantile_residuals` calculates multivariate quantile residuals (described by *Kalliovirta and Saikkonen 2010*) for a GMVAR model.

Usage

```
quantile_residuals(gmvar)
```

Arguments

`gmvar`	an object of class `'gmvar'` created with `fitGMVAR` or `GMVAR`.

Value

Returns $((n_obs - p)xd)$ matrix containing the multivariate quantile residuals, j:th column corresponds to the time series in the j:th column of the data. The multivariate quantile residuals are

calculated so that the first column quantile residuals are the "unconditioned ones" and the rest condition on all the previous ones in numerical order. Read the cited article by *Kalliovirta and Saikkonen 2010* for details.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Kalliovirta L. and Saikkonen P. 2010. Reliable Residuals for Multivariate Nonlinear Time Series Models. *Unpublished Revision of HECER Discussion Paper No. 247*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

fitGMVAR, GMVAR, quantile_residual_tests, diagnostic_plot, predict.gmvar, profile_logliks

Examples

```
# These examples use the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(1,2), d=2 model:
params122 <- c(0.623, -0.129, 0.959, 0.089, -0.006, 1.006, 1.746,
 0.804, 5.804, 3.245, 7.913, 0.952, -0.037, -0.019, 0.943, 6.926,
 3.982, 12.135, 0.789)
mod122 <- GMVAR(data, p=1, M=2, params=params122)
quantile_residuals(mod122)

# GMVAR(2,2), d=2 model with mean-parametrization:
params222 <- c(-11.904, 154.684, 1.314, 0.145, 0.094, 1.292, -0.389,
 -0.070, -0.109, -0.281, 0.920, -0.025, 4.839, 11.633, 124.983, 1.248,
  0.077, -0.040, 1.266, -0.272, -0.074, 0.034, -0.313, 5.855, 3.570,
  9.838, 0.740)
mod222 <- GMVAR(data, p=2, M=2, params=params222, parametrization="mean")
quantile_residuals(mod222)

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(1.03, 2.36, 1.79, 3, 1.25, 0.06, 0.04, 1.34, -0.29,
 -0.08, -0.05, -0.36, 1.2, 0.05, 0.05, 1.3, -0.3, -0.1, -0.05, -0.4,
  0.89, 0.72, -0.37, 2.16, 7.16, 1.3, 0.37)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
mod222s <- GMVAR(data, p=2, M=2, params=params222s, structural_pars=list(W=W_222))
quantile_residuals(mod222s)

# GMVAR(2,2), d=2 model with AR-parameters restricted to be
# the same for both regimes:
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
params222c <- c(1.031, 2.356, 1.786, 3.000, 1.250, 0.060, 0.036,
```

```
 1.335, -0.290, -0.083, -0.047, -0.356, 0.934, -0.152, 5.201, 5.883,
 3.560, 9.799, 0.368)
mod222c <- GMVAR(data, p=2, M=2, params=params222c, constraints=C_mat)
quantile_residuals(mod222c)

# GMVAR(2,2), d=2 model with AR-parameters restricted to be
# the same for both regimes and the non-diagonal elements of
# the coefficient matrices constrained to zero.
tmp <- matrix(c(1, rep(0, 10), 1, rep(0, 8), 1, rep(0, 10), 1),
 nrow=2*2^2, byrow=FALSE)
C_mat2 <- rbind(tmp, tmp)
params222c2 <- c(0.355, 3.193, -0.114, 2.829, 1.263, 1.338, -0.292,
 -0.362, 5.597, 3.456, 9.622, 0.982, -0.327, 5.236, 0.650)
mod222c2 <- GMVAR(data, p=2, M=2, params=params222c2,
  constraints=C_mat2)
quantile_residuals(mod222c)
```

`quantile_residuals_int` *Calculate multivariate quantile residuals of GMVAR model*

Description

`quantile_residuals_int` is a wrapper for `quantile_residuals` to compute quantile residuals using parameter values instead of class `gmvar` object.

Usage

```
quantile_residuals_int(
  data,
  p,
  M,
  params,
  conditional,
  parametrization,
  constraints = NULL,
  structural_pars = NULL
)
```

Arguments

`data`	a matrix or class `'ts'` object with `d>1` columns. Each column is taken to represent a single time series. `NA` values are not supported.
`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`params`	a real valued vector specifying the parameter values.
	For unconstrained models: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`conditional` a logical argument specifying whether the conditional or exact log-likelihood function should be used.

`parametrization`

`"mean"` or `"intercept"` determining whether the model is parametrized with regime means μ_m or intercept parameters $\phi_{m,0}$, m=1,...,M.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.

- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

Returns $((n_obs - p)xd)$ matrix containing the multivariate quantile residuals, j:th column corresponds to the time series in the j:th column of the data. The multivariate quantile residuals are calculated so that the first column quantile residuals are the "unconditioned ones" and the rest condition on all the previous ones in numerical order. Read the cited article by *Kalliovirta and Saikkonen 2010* for details.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Kalliovirta L. and Saikkonen P. 2010. Reliable Residuals for Multivariate Nonlinear Time Series Models. *Unpublished Revision of HECER Discussion Paper No. 247.*
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`random_coefmats` *Create random VAR-model* (dxd) *coefficient matrices* A*.*

Description

`random_coefmats` generates random VAR model coefficient matrices.

Usage

```
random_coefmats(d, how_many, scale)
```

Arguments

d	the number of time series in the system.
how_many	how many (dxd) coefficient matrices A should be drawn?
scale	non-diagonal elements will be drawn from mean zero normal distribution with sd=0.3/scale and diagonal elements from one with sd=0.6/scale. Larger scale will hence more likely result stationary coefficient matrices, but will explore smaller area of the parameter space. Can be for example 1 + log(2*mean(c((p-0.2)^(1.25),d)))

Value

Returns $((how_many * d^2)x1)$ vector containing vectorized coefficient matrices $(vec(A_1), ..., vec(A_{how_many}))$. Note that if how_many==p, then the returned vector equals ϕ_m.

---

random_coefmats2 *Create random stationary VAR model (dxd) coefficient matrices A.*

Description

random_coefmats2 generates random VAR model coefficient matrices.

Usage

```
random_coefmats2(p, d, ar_scale = 1)
```

Arguments

p	a positive integer specifying the autoregressive order of the model.
d	the number of time series in the system.
ar_scale	a positive real number. Larger values will typically result larger AR coefficients.

Details

The coefficient matrices are generated using the algorithm proposed by Ansley and Kohn (1986) which forces stationarity. It's not clear in detail how ar_scale affects the coefficient matrices. Read the cited article by Ansley and Kohn (1986) and the source code for more information.

Value

Returns $((pd^2)x1)$ vector containing stationary vectorized coefficient matrices $(vec(A_1), ..., vec(A_p)$.

References

- Ansley C.F., Kohn R. 1986. A note on reparameterizing a vector autoregressive moving average model to enforce stationarity. *Journal of statistical computation and simulation*, **24**:2, 99-106.

random_covmat *Create random VAR model error term covariance matrix*

Description

random_covmat generates random VAR model (dxd) error term covariance matrix Ω from (scaled) Wishart distribution for reduced form models and the parameters W,λ_1, ..., λ_M for structural models (from normal distributions).

Usage

```
random_covmat(d, M, omega_scale, W_scale, lambda_scale, structural_pars = NULL)
```

Arguments

d	the number of time series in the system.
M	a positive integer specifying the number of mixture components.
omega_scale	a size $(dx1)$ strictly positive vector specifying the scale and variability of the random covariance matrices in random mutations. The covariance matrices are drawn from (scaled) Wishart distribution. Expected values of the random covariance matrices are diag(omega_scale). Standard deviations of the diagonal elements are sqrt(2/d)*omega_scale[i] and for non-diagonal elements they are sqrt(1/d*omega_scale[i]*omega_scale[j]). Note that for d>4 this scale may need to be chosen carefully. Default in GAfit is var(stats::ar(data[,i],order.max=10)$resid This argument is ignored if structural model is considered.
W_scale	a size $(dx1)$ strictly positive vector partly specifying the scale and variability of the random covariance matrices in random mutations. The elements of the matrix W are drawn independently from such normal distributions that the expectation of the main **diagonal** elements of the first regime's error term covariance matrix $\Omega_1 = WW'$ is W_scale. The distribution of Ω_1 will be in some sense like a Wishart distribution but with the columns (elements) of W obeying the given constraints. The constraints are accounted for by setting the element to be always zero if it is subject to a zero constraint and for sign constraints the absolute value or negative the absolute value are taken, and then the variances of the elements of W are adjusted accordingly. This argument is ignored if reduced form model is considered.
lambda_scale	a length $M-1$ vector specifying the **standard deviation** of the mean zero normal distribution from which the eigenvalue λ_{mi} parameters are drawn from in random mutations. As the eigenvalues should always be positive, the absolute value is taken. The elements of lambda_scale should be strictly positive real numbers with the $m-1$th element giving the degrees of freedom for the mth regime. The expected value of the main **diagonal** elements ij of the mth $(m > 1)$ error term covariance matrix will be W_scale[i]*(d -n_i)^(-1)*sum(lambdas*ind_fun) where the $(dx1)$ vector lambdas is drawn from the absolute value of the t-distribution, n_i is the number of zero constraints in the ith row of W and ind_fun is an indicator function that takes the

value one iff the ijth element of W is not constrained to zero. Basically, larger lambdas (or smaller degrees of freedom) imply larger variance.

If the lambda parameters are **constrained** with the $(d(M-1)xr)$ constraint matrix C_lambda, then provide a length r vector specifying the standard deviation of the (absolute value of the) mean zero normal distribution each of the γ parameters are drawn from (the γ is a $(rx1)$ vector). The expected value of the main diagonal elements of the covariance matrices then depend on the constraints.

This argument is ignored if $M == 1$ or a reduced form model is considered. Default is `rep(3,times=M-1)` if lambdas are not constrained and `rep(3,times=r)` if lambdas are constrained.

As with omega_scale and W_scale, this argument should be adjusted carefully if specified by hand. **NOTE** that if lambdas are constrained in some other way than restricting some of them to be identical, this parameter should be adjusted accordingly in order to the estimation succeed!

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

For reduced form models: Returns a $(d(d+1)/2x1)$ vector containing vech-vectorized covariance matrix Ω.

For structural models: Returns a length $d^2 - n_zeros - d*(M-1)$ vector of the form $(Wvec(W), \lambda_2, ..., \lambda_M)$ where $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalue parameters of the mth regime $(m > 1)$ and n_zeros is the number of zero constraints in W. If lambdas are constrained, replacce $d * (M-1)$ in the length with r and $\lambda_2, ..., \lambda_M)$ with γ. The operator $Wvec()$ vectorizes a matrix and removes zeros.

`random_ind` *Create random mean-parametrized parameter vector of a GMVAR model that may not be stationary*

Description

random_ind generates random mean-parametrized parameter vector that may not be stationary.

Usage

```
random_ind(
  p,
  M,
  d,
  constraints = NULL,
  mu_scale,
  mu_scale2,
  omega_scale,
  W_scale,
  lambda_scale,
  structural_pars = NULL
)
```

Arguments

p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
d	the number of time series in the system.
constraints	a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= [I:...:I]' (Mpd^2xpd^2) where I = diag(p*d^2). Ignore (or set to NULL) if linear constraints should **not** be employed.
mu_scale	a size $(dx1)$ vector defining **means** of the normal distributions from which each mean parameter μ_m is drawn from in random mutations. Default is colMeans(data). Note that mean-parametrization is always used for optimization in GAfit - even when parametrization=="intercept". However, input (in initpop) and output (return value) parameter vectors can be intercept-parametrized.
mu_scale2	a size $(dx1)$ strictly positive vector defining **standard deviations** of the normal distributions from which each mean parameter μ_m is drawn from in random mutations. Default is 2*sd(data[,i]),i=1,..,d.
omega_scale	a size $(dx1)$ strictly positive vector specifying the scale and variability of the random covariance matrices in random mutations. The covariance matrices are drawn from (scaled) Wishart distribution. Expected values of the random covariance matrices are diag(omega_scale). Standard deviations of the diagonal elements are sqrt(2/d)*omega_scale[i] and for non-diagonal elements they are sqrt(1/d*omega_scale[i]*omega_scale[j]). Note that for d>4 this scale may need to be chosen carefully. Default in GAfit is var(stats::ar(data[,i],order.max=10)$resid This argument is ignored if structural model is considered.

`W_scale` a size $(dx1)$ strictly positive vector partly specifying the scale and variability of the random covariance matrices in random mutations. The elements of the matrix W are drawn independently from such normal distributions that the expectation of the main **diagonal** elements of the first regime's error term covariance matrix $\Omega_1 = WW'$ is `W_scale`. The distribution of Ω_1 will be in some sense like a Wishart distribution but with the columns (elements) of W obeying the given constraints. The constraints are accounted for by setting the element to be always zero if it is subject to a zero constraint and for sign constraints the absolute value or negative the absolute value are taken, and then the variances of the elements of W are adjusted accordingly. This argument is ignored if reduced form model is considered.

`lambda_scale` a length $M-1$ vector specifying the **standard deviation** of the mean zero normal distribution from which the eigenvalue λ_{mi} parameters are drawn from in random mutations. As the eigenvalues should always be positive, the absolute value is taken. The elements of `lambda_scale` should be strictly positive real numbers with the $m-1$th element giving the degrees of freedom for the mth regime. The expected value of the main **diagonal** elements ij of the mth $(m > 1)$ error term covariance matrix will be `W_scale[i]*(d-n_i)^(-1)*sum(lambdas*ind_fun)` where the $(dx1)$ vector `lambdas` is drawn from the absolute value of the t-distribution, `n_i` is the number of zero constraints in the ith row of W and `ind_fun` is an indicator function that takes the value one iff the ijth element of W is not constrained to zero. Basically, larger lambdas (or smaller degrees of freedom) imply larger variance.

If the lambda parameters are **constrained** with the $(d(M-1)xr)$ constraint matrix C_lambda, then provide a length r vector specifying the standard deviation of the (absolute value of the) mean zero normal distribution each of the γ parameters are drawn from (the γ is a $(rx1)$ vector). The expected value of the main diagonal elements of the covariance matrices then depend on the constraints.

This argument is ignored if $M == 1$ or a reduced form model is considered. Default is `rep(3,times=M-1)` if lambdas are not constrained and `rep(3,times=r)` if lambdas are constrained.

As with omega_scale and W_scale, this argument should be adjusted carefully if specified by hand. **NOTE** that if lambdas are constrained in some other way than restricting some of them to be identical, this parameter should be adjusted accordingly in order to the estimation succeed!

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

Returns random mean-parametrized parameter vector that has the same form as the argument `params` in the other functions, for instance, in the function `loglikelihood`.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`random_ind2` *Create somewhat random parameter vector of a GMVAR model that is always stationary*

Description

`random_ind2` generates random mean-parametrized parameter vector that is always stationary.

Usage

```
random_ind2(
  p,
  M,
  d,
  mu_scale,
  mu_scale2,
  omega_scale,
  ar_scale = 1,
  W_scale,
  lambda_scale,
  structural_pars = NULL
)
```

Arguments

`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`d`	the number of time series in the system.

`mu_scale` a size $(dx1)$ vector defining **means** of the normal distributions from which each mean parameter μ_m is drawn from in random mutations. Default is `colMeans(data)`. Note that mean-parametrization is always used for optimization in `GAfit` - even when `parametrization=="intercept"`. However, input (in `initpop`) and output (return value) parameter vectors can be intercept-parametrized.

`mu_scale2` a size $(dx1)$ strictly positive vector defining **standard deviations** of the normal distributions from which each mean parameter μ_m is drawn from in random mutations. Default is `2*sd(data[,i]),i=1,..,d`.

`omega_scale` a size $(dx1)$ strictly positive vector specifying the scale and variability of the random covariance matrices in random mutations. The covariance matrices are drawn from (scaled) Wishart distribution. Expected values of the random covariance matrices are `diag(omega_scale)`. Standard deviations of the diagonal elements are `sqrt(2/d)*omega_scale[i]` and for non-diagonal elements they are `sqrt(1/d*omega_scale[i]*omega_scale[j])`. Note that for `d>4` this scale may need to be chosen carefully. Default in `GAfit` is `var(stats::ar(data[,i],order.max=10)$resid` This argument is ignored if structural model is considered.

`ar_scale` a positive real number adjusting how large AR parameter values are typically generated in some random mutations. See the function `random_coefmats2` for details. This is ignored when estimating constrained models.

`W_scale` a size $(dx1)$ strictly positive vector partly specifying the scale and variability of the random covariance matrices in random mutations. The elements of the matrix W are drawn independently from such normal distributions that the expectation of the main **diagonal** elements of the first regime's error term covariance matrix $\Omega_1 = WW'$ is `W_scale`. The distribution of Ω_1 will be in some sense like a Wishart distribution but with the columns (elements) of W obeying the given constraints. The constraints are accounted for by setting the element to be always zero if it is subject to a zero constraint and for sign constraints the absolute value or negative the absolute value are taken, and then the variances of the elements of W are adjusted accordingly. This argument is ignored if reduced form model is considered.

`lambda_scale` a length $M-1$ vector specifying the **standard deviation** of the mean zero normal distribution from which the eigenvalue λ_{mi} parameters are drawn from in random mutations. As the eigenvalues should always be positive, the absolute value is taken. The elements of `lambda_scale` should be strictly positive real numbers with the $m-1$th element giving the degrees of freedom for the mth regime. The expected value of the main **diagonal** elements ij of the mth $(m > 1)$ error term covariance matrix will be `W_scale[i]*(d-n_i)^(-1)*sum(lambdas*ind_fun)` where the $(dx1)$ vector `lambdas` is drawn from the absolute value of the t-distribution, `n_i` is the number of zero constraints in the ith row of W and `ind_fun` is an indicator function that takes the value one iff the ijth element of W is not constrained to zero. Basically, larger lambdas (or smaller degrees of freedom) imply larger variance.

If the lambda parameters are **constrained** with the $(d(M-1)xr)$ constraint matrix C_lambda, then provide a length r vector specifying the standard deviation of the (absolute value of the) mean zero normal distribution each of the γ parameters are drawn from (the γ is a $(rx1)$ vector). The expected value of the main diagonal elements of the covariance matrices then depend on the constraints.

This argument is ignored if $M == 1$ or a reduced form model is considered. Default is `rep(3,times=M-1)` if lambdas are not constrained and `rep(3,times=r)` if lambdas are constrained.

As with omega_scale and W_scale, this argument should be adjusted carefully if specified by hand. **NOTE** that if lambdas are constrained in some other way than restricting some of them to be identical, this parameter should be adjusted accordingly in order to the estimation succeed!

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Details

The coefficient matrices are generated using the algorithm proposed by Ansley and Kohn (1986) which forces stationarity. It's not clear in detail how `ar_scale` exactly affects the coefficient matrices but larger `ar_scale` seems to result in larger AR coefficients. Read the cited article by Ansley and Kohn (1986) and the source code for more information.

The covariance matrices are generated from (scaled) Wishart distribution.

Models with AR parameters constrained are not supported!

Value

Returns random mean-parametrized parameter vector that has the same form as the argument `params` in the other functions, for instance, in the function `loglikelihood`.

References

- Ansley C.F., Kohn R. 1986. A note on reparameterizing a vector autoregressive moving average model to enforce stationarity. *Journal of statistical computation and simulation*, **24**:2, 99-106.
- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`reform_constrained_pars` *Reform constrained parameter vector into the "standard" form*

Description

`reform_constrained_pars` reforms constrained parameter vector into the form that corresponds to unconstrained parameter vectors.

Usage

```
reform_constrained_pars(
  p,
  M,
  d,
  params,
  constraints = NULL,
  structural_pars = NULL,
  change_na = FALSE
)
```

Arguments

`p`	a positive integer specifying the autoregressive order of the model.
`M`	a positive integer specifying the number of mixture components.
`d`	the number of time series in the system.
`params`	a real valued vector specifying the parameter values. **For unconstrained models:** Should be size $((M(pd^2+d+d(d+1)/2+1)-1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where • $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$ • ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$ • and $\sigma_m = vech(\Omega_m)$, m=1,...,M. **For constrained models:** Should be size $((M(d+d(d+1)/2+1)+q-1)x1)$ and have form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where • ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix. **For structural GMVAR model:** Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where • $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component. **If AR parameters are constrained:** Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above. **If W is constrained:** Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace λ_2, ...,λ_M with γ $(rx1)$ that satisfies (λ_2, ..., λ_M) $= C_\lambda \gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form (ϕ_1, ...,ϕ_M) $=C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies (λ_2, ..., λ_M) $= C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

`change_na` change NA parameter values of constrained models to -9.999?

Value

Returns "regular model" parameter vector corresponding to the constraints.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`reform_data` *Reform data*

Description

`reform_data` reforms the data into a form that is easier to use when calculating log-likelihood values etc.

Usage

```
reform_data(data, p)
```

Arguments

`data`	a matrix or class `'ts'` object with `d>1` columns. Each column is taken to represent a single time series. `NA` values are not supported.
`p`	a positive integer specifying the autoregressive order of the model.

Value

Returns the data reformed into a $((n_obs - p + 1)x(dp))$ matrix. The i:th row of the matrix contains the vector $(y'_{i-1}, ..., y'_{i-p})$ $((dp)x1)$, where $y_i = (y_{1i}, ..., y_{di})$ $(dx1)$.

Warning

No argument checks!

`reform_structural_pars`
Reform structural parameter vector into the "standard" form

Description

`reform_structural_pars` reforms (unconstrained) structural parameter vector into the form that corresponds to reduced form parameter vectors.

Usage

```
reform_structural_pars(p, M, d, params, structural_pars = NULL)
```

Arguments

`p` a positive integer specifying the autoregressive order of the model.

`M` a positive integer specifying the number of mixture components.

`d` the number of time series in the system.

`params` a real valued vector specifying the parameter values.

For unconstrained models: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d + d(d+1)/2 + 1) + q - 1)x1)$ and have form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M)$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where γ is the new $(rx1)$ parameter subject to which the model is

estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Details

If the structural parameter vector is a constrained one, use `reform_constrained_pars` first to remove the constraints.

Value

Returns (unconstrained) "reduced form model" parameter vector.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`regime_distance` *Calculate "distance" between two (scaled) regimes* $\upsilon\_m = (\phi\_m, 0, \phi\_m, \sigma\_m)$

Description

`regime_distance` calculates "distance" between two scaled regimes. This is used in the genetic algorithm.

Usage

```
regime_distance(regime_pars1, regime_pars2)
```

Arguments

`regime_pars1`	a length $pd^2 + d + d(d+1)/2$ vector $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$.
`regime_pars2`	a length $pd^2 + d + d(d+1)/2$ vector $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$.

Value

Returns "distance" between `regime_pars1` and `regime_pars2`. Values are scaled before calculating the "distance". Read the source code for more details.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`reorder_W_columns` *Reorder columns of the W-matrix and lambda parameters of a structural GMVAR model.*

Description

`reorder_W_columns` reorder columns of the W-matrix and lambda parameters of a structural GMVAR model.

Usage

```
reorder_W_columns(gmvar, perm)
```

Arguments

`gmvar`	an object of class `'gmvar'` created with `fitGMVAR` or `GMVAR`.
`perm`	an integer vector of length d specifying the new order of the columns of W. Also lambda parameters of each regime will be reordered accordingly.

Details

The order of the columns of W can be changed without changing the implied reduced form model as long as the order of lambda parameters is also changed accordingly. Note that the constraints imposed on W (or the B-matrix) will also be modified accordingly.

This function does not support models with constraints imposed on the lambda parameters!

Also all signs in any column of W can be swapped (without changing the implied reduced form model) with the function `swap_W_signs` but this obviously also swaps the sign constraints in the corresponding columns of W.

Value

Returns an object of class `'gmvar'` defining a structural GMVAR model with the modified structural parameters and constraints.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

`fitGMVAR`, `GMVAR`, `GIRF`, `gmvar_to_sgmvar`, `swap_W_signs`

Examples

```
# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(-11.964, 155.024, 11.636, 124.988, 1.314, 0.145, 0.094, 1.292,
 -0.389, -0.07, -0.109, -0.281, 1.248, 0.077, -0.04, 1.266, -0.272, -0.074,
  0.034, -0.313, 0.903, 0.718, -0.324, 2.079, 7.00, 1.44, 0.742)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
mod222s <- GMVAR(p=2, M=2, d=2, params=params222s, parametrization="mean",
                 structural_pars=list(W=W_222))
mod222s

# The same reduced form model, modified W and lambda:
reorder_W_columns(mod222s, perm=2:1)
```

`simulateGMVAR` *Simulate from GMVAR process*

Description

`simulateGMVAR` simulates observations from a GMVAR process.

Usage

```
simulateGMVAR(
  gmvar,
  nsimu,
  init_values = NULL,
  ntimes = 1,
  drop = TRUE,
  seed = NULL,
  girf_pars = NULL
)
```

Arguments

gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.
nsimu	number of observations to be simulated.
init_values	a size (pxd) matrix specifying the initial values to be used in the simulation, where d is the number of time series in the system. The **last** row will be used as initial values for the first lag, the second last row for second lag etc. If not specified, initial values will be drawn from the stationary distribution of the process.
ntimes	how many sets of simulations should be performed?
drop	if TRUE (default) then the components of the returned list are coerced to lower dimension if ntimes==1, i.e., $sample and $mixing_weights will be matrices, and $component will be vector.
seed	set seed for the random number generator?
girf_pars	This argument is used internally in the estimation of generalized impulse response functions (see ?GIRF). You should ignore it.

Details

The argument ntimes is intended for forecasting: a GMVAR process can be forecasted by simulating its possible future values. One can easily perform a large number simulations and calculate the sample quantiles from the simulated values to obtain prediction intervals (see the forecasting example).

Value

If drop==TRUE and ntimes==1 (default): $sample, $component, and $mixing_weights are matrices. Otherwise, returns a list with...

$sample a size (nsimu$xdx$ntimes) array containing the samples: the dimension [t,,] is the time index, the dimension [,d,] indicates the marginal time series, and the dimension [,,i] indicates the i:th set of simulations.

$component a size (nsimu$x$ntimes) matrix containing the information from which mixture component each value was generated from.

$mixing_weights a size (nsimu$xM x$ntimes) array containing the mixing weights corresponding to the sample: the dimension [t,,] is the time index, the dimension [,m,] indicates the regime, and the dimension [,,i] indicates the i:th set of simulations.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

fitGMVAR, GMVAR, diagnostic_plot, predict.gmvar, profile_logliks, quantile_residual_tests, GIRF

Examples

```
# These examples use the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(1,2), d=2 process, initial values from the stationary
# distribution
params122 <- c(0.623, -0.129, 0.959, 0.089, -0.006, 1.006, 1.746,
 0.804, 5.804, 3.245, 7.913, 0.952, -0.037, -0.019, 0.943, 6.926,
 3.982, 12.135, 0.789)
mod122 <- GMVAR(p=1, M=2, d=2, params=params122)
set.seed(1)
sim122 <- simulateGMVAR(mod122, nsimu=500)
plot.ts(sim122$sample)
ts.plot(sim122$mixing_weights, col=c("blue", "red"), lty=2)
plot(sim122$component, type="l")

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(-11.964, 155.024, 11.636, 124.988, 1.314, 0.145, 0.094, 1.292,
  -0.389, -0.07, -0.109, -0.281, 1.248, 0.077, -0.04, 1.266, -0.272, -0.074,
  0.034, -0.313, 0.903, 0.718, -0.324, 2.079, 7.00, 1.44, 0.742)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
mod222s <- GMVAR(data, p=2, M=2, params=params222s, parametrization="mean",
structural_pars=list(W=W_222))
sim222s <- simulateGMVAR(mod222s, nsimu=100)
plot.ts(sim222s$sample)

## FORECASTING EXAMPLE ##
# Forecast 5-steps-ahead, 10000 sets of simulations with initial
# values from the data:
# GMVAR(2,2), d=2 model with mean-parametrization:
params222 <- c(-11.904, 154.684, 1.314, 0.145, 0.094, 1.292, -0.389,
 -0.070, -0.109, -0.281, 0.920, -0.025, 4.839, 11.633, 124.983, 1.248,
  0.077, -0.040, 1.266, -0.272, -0.074, 0.034, -0.313, 5.855, 3.570,
  9.838, 0.740)
mod222 <- GMVAR(data, p=2, M=2, params=params222, parametrization="mean")
sim222 <- simulateGMVAR(mod222, nsimu=5, ntimes=10000)

# Point forecast + 95% prediction intervals:
apply(sim222$sample, 1:2, quantile, probs=c(0.025, 0.5, 0.972))

# Similar forecast for the mixing weights:
apply(sim222$mixing_weights, 1:2, quantile, probs=c(0.025, 0.5, 0.972))


# GMVAR(2,2), d=2 model with AR parameters restricted to be
# the same for both regimes, custom inital values:
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
params222c <- c(1.031, 2.356, 1.786, 3.000, 1.250, 0.060, 0.036,
 1.335, -0.290, -0.083, -0.047, -0.356, 0.934, -0.152, 5.201, 5.883,
```

```
 3.560, 9.799, 0.368)
mod222c <- GMVAR(data, p=2, M=2, params=params222c, constraints=C_mat)
sim222c <- simulateGMVAR(mod222c, nsimu=100,
            init_values=matrix(c(30, 30, 80, 80), nrow=2))
plot.ts(sim222c$sample)
ts.plot(sim222c$mixing_weights, col=c("blue", "red"), lty=2)
plot(sim222c$component, type="l")
```

`smart_covmat` *Create random VAR-model (dxd) error term covariance matrix Ω fairly close to a given* **positive definite** *covariance matrix using (scaled) Wishart distribution*

Description

`random_covmat` generates random VAR model (dxd) error term covariance matrix Ω from (scaled) Wishart distribution that is fairly close to the given matrix.

Usage

```
smart_covmat(d, M, Omega, W_and_lambdas, accuracy, structural_pars = NULL)
```

Arguments

`d`	the number of time series in the system.
`M`	a positive integer specifying the number of mixture components.
`Omega`	a symmetric positive definite (dxd) covariance matrix specifying expected value of the matrix to be generated.
`W_and_lambdas`	the mean of the normal distribution the new parameters are generated from. **If lambdas are not constrained:** a size $(d^2 - n_zeros + d*(M-1))$ vector $(Wvec(W), \lambda_2, ..., \lambda M)$, where n_zeros is the number of zero constraints in W and $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$. **If lambdas are constrained:** a size $(d^2 - n_zeros + r)$ vector $(Wvec(W), \gamma)$, where $C_\lambda \gamma = (\lambda_2, ..., \lambda_M)$, γ is of the size $(rx1)$, and C_λ of the size $(d*(M-1)xr)$.
`accuracy`	a positive real number adjusting how close to the given covariance matrix the returned individual should be. For **reduced form models** standard deviation of each diagonal element is for reduced form models • $\omega_{i,i}$/`accuracy` when `accuracy > d/2` • and `sqrt(2/d)*`$\omega_{i,i}$ when `accuracy <= d/2`. Wishart distribution is used for reduced form models, but for more details read the source code. For **structural models**, the parameters are generated from normal distribution with mean given by the argument `W_and_lambdas` and the standard deviation is `sqrt(abs(W_and_lambdas)/(d + accuracy))`.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

For reduced form models: Returns a $(d(d+1)/2x1)$ vector containing vech-vectorized covariance matrix Ω.

For structural models: Returns a length $d^2 - n_zeros - d*(M-1)$ vector of the form $(Wvec(W), \lambda_2, ..., \lambda_M)$ where $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalue parameters of the mth regime $(m > 1)$ and n_zeros is the number of zero constraints in W. If lambdas are constrained, replacce $d * (M-1)$ in the length with r and $\lambda_2, ..., \lambda_M)$ with γ. The operator $Wvec()$ vectorizes a matrix and removes zeros.

`smart_ind` *Create random parameter vector of a GMVAR model fairly close to a given parameter vector*

Description

`smart_ind` creates random mean-parametrized parameter vector of a GMVAR model fairly close to a given parameter vector. The result may not be stationary.

Usage

```
smart_ind(
  p,
  M,
  d,
  params,
  constraints = NULL,
  accuracy = 1,
  which_random = numeric(0),
  mu_scale,
```

```
  mu_scale2,
  omega_scale,
  ar_scale = 1,
  W_scale,
  lambda_scale,
  structural_pars = NULL
)
```

Arguments

p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
d	the number of time series in the system.
params	a real valued vector specifying the parameter values. **For reduced form model:** Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, $\alpha_1, ..., \alpha_{M-1}$), where: • $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$ • $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})$ • and $\sigma_m = vech(\Omega_m)$, m=1,...,M. **For structural GMVAR model:** Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where • $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component. Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the i:th coefficient matrix of the m:th mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with the regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by KMS (2016) introducing the GMVAR model.
constraints	a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form (ϕ_1, ...,ϕ_M) =$C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.
accuracy	a positive real number adjusting how close to the given parameter vector the returned individual should be. Larger number means larger accuracy. Read the source code for details.
which_random	a vector with length between 1 and M specifying the mixture components that should be random instead of close to the given parameter vector. This does not consider constrained AR or lambda parameters.

`mu_scale` a size $(dx1)$ vector defining **means** of the normal distributions from which each mean parameter μ_m is drawn from in random mutations. Default is `colMeans(data)`. Note that mean-parametrization is always used for optimization in `GAfit` - even when `parametrization=="intercept"`. However, input (in `initpop`) and output (return value) parameter vectors can be intercept-parametrized.

`mu_scale2` a size $(dx1)$ strictly positive vector defining **standard deviations** of the normal distributions from which each mean parameter μ_m is drawn from in random mutations. Default is `2*sd(data[,i]),i=1,..,d`.

`omega_scale` a size $(dx1)$ strictly positive vector specifying the scale and variability of the random covariance matrices in random mutations. The covariance matrices are drawn from (scaled) Wishart distribution. Expected values of the random covariance matrices are `diag(omega_scale)`. Standard deviations of the diagonal elements are `sqrt(2/d)*omega_scale[i]` and for non-diagonal elements they are `sqrt(1/d*omega_scale[i]*omega_scale[j])`. Note that for `d>4` this scale may need to be chosen carefully. Default in `GAfit` is `var(stats::ar(data[,i],order.max=10)$resid` This argument is ignored if structural model is considered.

`ar_scale` a positive real number adjusting how large AR parameter values are typically generated in some random mutations. See the function `random_coefmats2` for details. This is ignored when estimating constrained models.

`W_scale` a size $(dx1)$ strictly positive vector partly specifying the scale and variability of the random covariance matrices in random mutations. The elements of the matrix W are drawn independently from such normal distributions that the expectation of the main **diagonal** elements of the first regime's error term covariance matrix $\Omega_1 = WW'$ is `W_scale`. The distribution of Ω_1 will be in some sense like a Wishart distribution but with the columns (elements) of W obeying the given constraints. The constraints are accounted for by setting the element to be always zero if it is subject to a zero constraint and for sign constraints the absolute value or negative the absolute value are taken, and then the variances of the elements of W are adjusted accordingly. This argument is ignored if reduced form model is considered.

`lambda_scale` a length $M-1$ vector specifying the **standard deviation** of the mean zero normal distribution from which the eigenvalue λ_{mi} parameters are drawn from in random mutations. As the eigenvalues should always be positive, the absolute value is taken. The elements of `lambda_scale` should be strictly positive real numbers with the $m-1$th element giving the degrees of freedom for the mth regime. The expected value of the main **diagonal** elements ij of the mth $(m > 1)$ error term covariance matrix will be `W_scale[i]*(d-n_i)^(-1)*sum(lambdas*ind_fun)` where the $(dx1)$ vector `lambdas` is drawn from the absolute value of the t-distribution, `n_i` is the number of zero constraints in the ith row of W and `ind_fun` is an indicator function that takes the value one iff the ijth element of W is not constrained to zero. Basically, larger lambdas (or smaller degrees of freedom) imply larger variance.

If the lambda parameters are **constrained** with the $(d(M-1)xr)$ constraint matrix C_lambda, then provide a length r vector specifying the standard deviation of the (absolute value of the) mean zero normal distribution each of the γ parameters are drawn from (the γ is a $(rx1)$ vector). The expected value of the main diagonal elements of the covariance matrices then depend on the constraints.

This argument is ignored if $M == 1$ or a reduced form model is considered. Default is `rep(3,times=M-1)` if lambdas are not constrained and `rep(3,times=r)` if lambdas are constrained.

As with omega_scale and W_scale, this argument should be adjusted carefully if specified by hand. **NOTE** that if lambdas are constrained in some other way than restricting some of them to be identical, this parameter should be adjusted accordingly in order to the estimation succeed!

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

Returns random mean-parametrized parameter vector that has the same form as the argument `params` in the other functions, for instance, in the function `loglikelihood`.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`sort_components` *Sort components in parameter vector according to mixing weights into a decreasing order*

Description

`sort_components` sorts mixture components in the parameter vector according to mixing weights into a decreasing order.

Usage

```
sort_components(p, M, d, params, structural_pars = NULL)
```

Arguments

p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
d	the number of time series in the system.
params	a real valued vector specifying the parameter values. **For reduced form model:** Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where: • $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$ • ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$ • and $\sigma_m = vech(\Omega_m)$, m=1,...,M. **For structural GMVAR model:** Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M$ where • $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component. Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the i:th coefficient matrix of the m:th mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with the regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by KMS (2016) introducing the GMVAR model.
structural_pars	If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements: • `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero. • `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained. See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Details

Constrained parameter vectors are not supported (expect for constraints in W)! For structural models, the order of the first mixture component is fixed by construction, so the rest $m = 2, ..., M$ mixture components are rearranged only by the mixing weight parameters.

Value

Returns sorted parameter vector...

For reduced form GMVAR model: ...with $\alpha_1 > ... > \alpha_M$, that has form θ=(υ_1,...,υ_M, $\alpha_1, ..., \alpha_{M-1}$), where:

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,1})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For structural GMVAR model: ...with $\alpha_2 > ... > \alpha_M$, that has form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M, \alpha_1$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the i:th coefficient matrix of the m:th component, Ω_m denotes the error term covariance matrix of the m:th component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped.

$vec()$ is vectorization operator that stack columns of the given matrix into a vector. $vech()$ stacks columns of the given matrix from the principal diagonal downwards (including elements on the diagonal) to form a vector. The notation is in line with the cited article by KMS (2016) introducing the GMVAR model.

Warning

No argument checks!

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`standard_errors` *Calculate standard errors for estimates of GMVAR model*

Description

`standard_errors` numerically calculates approximate standard errors for the GMVAR model using square roots of the diagonal of inverse of observed information matrix.

Usage

```
standard_errors(
  data,
  p,
  M,
  params,
  conditional = TRUE,
  parametrization = c("intercept", "mean"),
  constraints = NULL,
  structural_pars = NULL,
  minval
)
```

Arguments

data	a matrix or class 'ts' object with d>1 columns. Each column is taken to represent a single time series. NA values are not supported.
p	a positive integer specifying the autoregressive order of the model.
M	a positive integer specifying the number of mixture components.
params	a real valued vector specifying the parameter values.

For unconstrained models: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- ϕ_m= $(vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d + d(d+1)/2 + 1) + q - 1)x1)$ and have form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form θ= $(\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M)$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace λ_2, ...,λ_M with γ $(rx1)$ that satisfies (λ_2, ..., λ_M) $= C_\lambda \gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If parametrization=="mean", just replace each $\phi_{m,0}$ with regimewise mean μ_m.

$vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`conditional` a logical argument specifying whether the conditional or exact log-likelihood function should be used.

`parametrization`

`"mean"` or `"intercept"` determining whether the model is parametrized with regime means μ_m or intercept parameters $\phi_{m,0}$, m=1,...,M.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda\gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

`minval` the value that will be returned if the parameter vector does not lie in the parameter space (excluding the identification condition).

Value

A vector containing the approximate standard errors of the estimates.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

swap_parametrization *Swap the parametrization of a GMVAR model*

Description

swap_parametrization swaps the parametrization of a GMVAR model to "mean" if the current parametrization is "intercept", and vice versa.

Usage

```
swap_parametrization(gmvar)
```

Arguments

gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.

Details

swap_parametrization is a convenient tool if you have estimated the model in "intercept"-parametrization, but wish to work with "mean"-parametrization in the future, or vice versa. In gmvarkit, the approximate standard errors are only available for parametrized parameters.

Value

Returns an object of class 'gmvar' defining the specified reduced form or structural GMVAR model. Can be used to work with other functions provided in gmvarkit.

Remark that the first autocovariance/correlation matrix in $uncond_moments is for the lag zero, the second one for the lag one, etc.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Kalliovirta L. and Saikkonen P. 2010. Reliable Residuals for Multivariate Nonlinear Time Series Models. *Unpublished Revision of HECER Discussion Paper No. 247*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

fitGMVAR, GMVAR, iterate_more

Examples

```
# These examples use the data 'eurusd' which comes with the
# package, but in a scaled form.
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# GMVAR(1,2), d=2 model:
params122 <- c(0.623, -0.129, 0.959, 0.089, -0.006, 1.006, 1.746,
 0.804, 5.804, 3.245, 7.913, 0.952, -0.037, -0.019, 0.943, 6.926,
 3.982, 12.135, 0.789)
mod122 <- GMVAR(data, p=1, M=2, params=params122)
mod122 # intercept parametrization

mod122_2 <- swap_parametrization(mod122)
mod122_2 # mean parametrization


# GMVAR(2,2), d=2 model:
params222 <- c(-11.904, 154.684, 1.314, 0.145, 0.094, 1.292, -0.389,
 -0.070, -0.109, -0.281, 0.920, -0.025, 4.839, 11.633, 124.983, 1.248,
  0.077, -0.040, 1.266, -0.272, -0.074, 0.034, -0.313, 5.855, 3.570,
  9.838, 0.740)
mod222 <- GMVAR(data, p=2, M=2, params=params222, parametrization="mean")
mod222 # mean parametrization

mod222_2 <- swap_parametrization(mod222)
mod222_2 # intercept parametrization

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(1.03, 2.36, 1.79, 3, 1.25, 0.06, 0.04, 1.34, -0.29,
 -0.08, -0.05, -0.36, 1.2, 0.05, 0.05, 1.3, -0.3, -0.1, -0.05, -0.4,
  0.89, 0.72, -0.37, 2.16, 7.16, 1.3, 0.37)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
mod222s <- GMVAR(data, p=2, M=2, params=params222s, parametrizatio="intercept",
 structural_pars=list(W=W_222))
mod222s # intercept parametrization

mod222s_2 <- swap_parametrization(mod222s)
mod222s_2 # mean parametrization
```

---

swap_W_signs *Swap all signs in pointed columns a the W matrix of a structural GMVAR model.*

Description

`swap_W_signs` swaps all signs in pointed columns a the W matrix of a structural GMVAR model. Consequently, signs in the columns of the B-matrix are also swapped accordingly.

Usage

```
swap_W_signs(gmvar, which_to_swap)
```

Arguments

gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.
which_to_swap	a numeric vector of length at most d and elemnts in $1, .., d$ specifying the columns of W whose sign should be swapped.

Details

All signs in any column of W can be swapped without changing the implied reduced form model. Consequently, also the signs in the columns of the B-matrix are swapped. Note that the sign constraints imposed on W (or the B-matrix) are also swapped in the corresponding columns accordingly.

Also the order of the columns of W can be changed (without changing the implied reduced form model) as long as the order of lambda parameters is also changed accordingly. This can be done with the function reorder_W_columns.

Value

Returns an object of class 'gmvar' defining a structural GMVAR model with the modified structural parameters and constraints.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

fitGMVAR, GMVAR, GIRF, reorder_W_columns, gmvar_to_sgmvar

Examples

```
# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(-11.964, 155.024, 11.636, 124.988, 1.314, 0.145, 0.094, 1.292,
 -0.389, -0.07, -0.109, -0.281, 1.248, 0.077, -0.04, 1.266, -0.272, -0.074,
  0.034, -0.313, 0.903, 0.718, -0.324, 2.079, 7.00, 1.44, 0.742)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
mod222s <- GMVAR(p=2, M=2, d=2, params=params222s, parametrization="mean",
                 structural_pars=list(W=W_222))
mod222s

# The same reduced form model, with signs in the second column of W swapped:
swap_W_signs(mod222s, which_to_swap=2)
```

```
# The same reduced form model, with signs in both column of W swapped:
swap_W_signs(mod222s, which_to_swap=1:2)
```

---

uncond_moments *Calculate the unconditional mean, variance, the first p autocovariances, and the first p autocorrelations of a GMVAR process*

Description

uncond_moments calculates the unconditional mean, variance, the first p autocovariances, and the first p autocorrelations of the given GMVAR process.

Usage

```
uncond_moments(gmvar)
```

Arguments

gmvar	an object of class 'gmvar' created with fitGMVAR or GMVAR.

Details

The unconditional moments are based on the stationary distribution of the process.

Value

Returns a list with three components:

$uncond_mean a length d vector containing the unconditional mean of the process.

$autocovs an $(dxdxp + 1)$ array containing the lag 0,1,...,p autocovariances of the process. The subset [,,j] contains the lag j-1 autocovariance matrix (lag zero for the variance).

$autocors the autocovariance matrices scaled to autocorrelation matrices.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

Other moment functions: cond_moments(), get_regime_autocovs(), get_regime_means()

Examples

```
# GMVAR(1,2), d=2 model:
params122 <- c(0.623, -0.129, 0.959, 0.089, -0.006, 1.006, 1.746,
 0.804, 5.804, 3.245, 7.913, 0.952, -0.037, -0.019, 0.943, 6.926,
 3.982, 12.135, 0.789)
mod122 <- GMVAR(p=1, M=2, d=2, params=params122)
uncond_moments(mod122)

# GMVAR(2,2), d=2 model with AR-parameters restricted to be
# the same for both regimes:
C_mat <- rbind(diag(2*2^2), diag(2*2^2))
params222c <- c(1.031, 2.356, 1.786, 3.000, 1.250, 0.060, 0.036,
 1.335, -0.290, -0.083, -0.047, -0.356, 0.934, -0.152, 5.201, 5.883,
 3.560, 9.799, 0.368)
mod222c <- GMVAR(p=2, M=2, d=2, params=params222c, constraints=C_mat)
uncond_moments(mod222c)

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
params222s <- c(1.03, 2.36, 1.79, 3, 1.25, 0.06, 0.04, 1.34, -0.29,
 -0.08, -0.05, -0.36, 1.2, 0.05, 0.05, 1.3, -0.3, -0.1, -0.05, -0.4,
  0.89, 0.72, -0.37, 2.16, 7.16, 1.3, 0.37)
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
mod222s <- GMVAR(p=2, M=2, d=2, params=params222s, structural_pars=list(W=W_222))
uncond_moments(mod222s)
```

---

uncond_moments_int *Calculate the unconditional mean, variance, the first p autocovariances, and the first p autocorrelations of a GMVAR process*

Description

uncond_moments_int calculates the unconditional mean, variance, the first p autocovariances, and the first p autocorrelations of the specified GMVAR process.

Usage

```
uncond_moments_int(
  p,
  M,
  d,
  params,
  parametrization = c("intercept", "mean"),
  constraints = NULL,
  structural_pars = NULL
)
```

Arguments

`p` a positive integer specifying the autoregressive order of the model.

`M` a positive integer specifying the number of mixture components.

`d` the number of time series in the system.

`params` a real valued vector specifying the parameter values.

For unconstrained models: Should be size $((M(pd^2 + d + d(d+1)/2 + 1) - 1)x1)$ and have form θ=(υ_1, ...,υ_M, α_1, ..., α_{M-1}), where

- $\upsilon_m = (\phi_{m,0}, \phi_m, \sigma_m)$
- $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p})$
- and $\sigma_m = vech(\Omega_m)$, m=1,...,M.

For constrained models: Should be size $((M(d + d(d+1)/2 + 1) + q - 1)x1)$ and have form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \psi, \sigma_1, ..., \sigma_M, \alpha_1, ..., \alpha_{M-1})$, where

- ψ $(qx1)$ satisfies $(\phi_1, ..., \phi_M) = C\psi$ where C is (Mpd^2xq) constraint matrix.

For structural GMVAR model: Should have the form $\theta = (\phi_{1,0}, ..., \phi_{M,0}, \phi_1, ..., \phi_M, vec(W), \lambda_2, ..., \lambda_M)$ where

- $\lambda_m = (\lambda_{m1}, ..., \lambda_{md})$ contains the eigenvalues of the mth mixture component.

If AR parameters are constrained: Replace $\phi_1, ..., \phi_M$ with ψ $(qx1)$ that satisfies $(\phi_1, ..., \phi_M) = C\psi$, as above.

If W is constrained: Remove the zeros from $vec(W)$ and make sure the other entries satisfy the sign constraints.

If λ_{mi} are constrained: Replace $\lambda_2, ..., \lambda_M$ with γ $(rx1)$ that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where C_λ is a $(d(M-1)xr)$ constraint matrix.

Above, $\phi_{m,0}$ is the intercept parameter, $A_{m,i}$ denotes the ith coefficient matrix of the mth mixture component, Ω_m denotes the error term covariance matrix of the m:th mixture component, and α_m is the mixing weight parameter. The W and λ_{mi} are structural parameters replacing the error term covariance matrices (see Virolainen, 2020). If $M = 1$, α_m and λ_{mi} are dropped. If `parametrization=="mean"`, just replace each $\phi_{m,0}$ with regimewise mean μ_m. $vec()$ is vectorization operator that stacks columns of a given matrix into a vector. $vech()$ stacks columns of a given matrix from the principal diagonal downwards (including elements on the diagonal) into a vector. The notation is in line with the cited article by *Kalliovirta, Meitz and Saikkonen (2016)* introducing the GMVAR model.

`parametrization`

`"mean"` or `"intercept"` determining whether the model is parametrized with regime means μ_m or intercept parameters $\phi_{m,0}$, m=1,...,M.

`constraints` a size (Mpd^2xq) constraint matrix C specifying general linear constraints to the autoregressive parameters. We consider constraints of form $(\phi_1, ..., \phi_M) = C\psi$, where $\phi_m = (vec(A_{m,1}), ..., vec(A_{m,p}))(pd^2x1), m = 1, ..., M$, contains the coefficient matrices and ψ $(qx1)$ contains the related parameters. For example, to restrict the AR-parameters to be the same for all regimes, set C= `[I:...:I]'` (Mpd^2xpd^2) where `I = diag(p*d^2)`. Ignore (or set to `NULL`) if linear constraints should **not** be employed.

`structural_pars`

If `NULL` a reduced form model is considered. For structural model, should be a list containing the following elements:

- `W` - a (dxd) matrix with its entries imposing constraints on W: `NA` indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero.
- `C_lambda` - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of `C_lambda` must be either **positive** or **zero**. Ignore (or set to `NULL`) if the eigenvalues λ_{mi} should not be constrained.

See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Details

The unconditional moments are based on the stationary distribution of the process.

Value

Returns a list with three components:

`$uncond_mean` a length d vector containing the unconditional mean of the process.

`$autocovs` an $(dxdxp + 1)$ array containing the lag 0,1,...,p autocovariances of the process. The subset `[,,j]` contains the lag `j-1` autocovariance matrix (lag zero for the variance).

`$autocors` the autocovariance matrices scaled to autocorrelation matrices.

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Lütkepohl H. 2005. New Introduction to Multiple Time Series Analysis, *Springer*.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

`unvec` *Reverse vectorization operator*

Description

`unvec` forms a square matrix from a vector of stacked columns, stacked by `vec`.

Usage

```
unvec(d, a)
```

Arguments

d	the number of rows in the square matrix to be formed.
a	a size (d^2x1) vector to be unvectorized into a (dxd) matrix.

Value

a matrix of size (dxd).

Warning

No argument checks!

---

unvech *Reverse operator of the parsimonious vectorization operator* vech

---

Description

unvech creates a symmetric matrix from the given vector by copying the lower triangular part to be the upper triangular part as well.

Usage

```
unvech(d, a)
```

Arguments

d	number of rows the square matrix to be formed.
a	a size $(d(d+1)/2x1)$ vector to be unvectorized into a symmetric (dxd) matrix.

Value

a symmetric matrix of size (dxd).

Warning

No argument checks!

unWvec *Reverse vectorization operator that restores zeros*

Description

unWvec forms a square matrix from a vector of stacked columns where zeros are removed according to structural parameter constaints.

Usage

```
unWvec(Wvector, d, structural_pars = NULL)
```

Arguments

Wvector	a length $d^2 - n_zeros$ vector where n_zeros is the number of zero entries in the matrix W.
d	the number of rows in the square matrix to be formed.
structural_pars	If NULL a reduced form model is considered. For structural model, should be a list containing the following elements: • W - a (dxd) matrix with its entries imposing constraints on W: NA indicating that the element is unconstrained, a positive value indicating strict positive sign constraint, a negative value indicating strict negative sign constraint, and zero indicating that the element is constrained to zero. • C_lambda - a $(d(M-1)xr)$ constraint matrix that satisfies $(\lambda_2, ..., \lambda_M) = C_\lambda \gamma$ where γ is the new $(rx1)$ parameter subject to which the model is estimated (similarly to AR parameter constraints). The entries of C_lambda must be either **positive** or **zero**. Ignore (or set to NULL) if the eigenvalues λ_{mi} should not be constrained. See Virolainen (2020) for the conditions required to identify the shocks and for the B-matrix as well (it is W times a time-varying diagonal matrix with positive diagonal entries).

Value

a (dxd) matrix W.

Warning

No argument checks!

vec *Vectorization operator*

Description

vec stacks columns of the given matrix to form a vector.

Usage

```
vec(A)
```

Arguments

A	a size (dxd) square matrix to be vectorized.

Value

a vector of size (d^2x1).

Warning

No argument checks!

vech *Parsimonious vectorization operator for symmetric matrices*

Description

vech stacks columns of the given matrix from the principal diagonal downwards (including elements on the diagonal) to form a vector.

Usage

```
vech(A)
```

Arguments

A	a size (dxd) symmetric matrix to be vectorized parsimoniously.

Value

a vector of size $(d(d+1)/2x1)$.

Warning

No argument checks!

`Wald_test` *Perform Wald test for a GMVAR or SGMVAR model*

Description

`Wald_test` performs a Wald test for a GMVAR or SGMVAR model

Usage

```
Wald_test(gmvar, A, c, h = 6e-06)

## S3 method for class 'wald'
print(x, ..., digits = 4)
```

Arguments

`gmvar`	an object of class `'gmvar'` created with `fitGMVAR` or `GMVAR`.
`A`	a size (kxn_params) matrix with full row rank specifying part of the null hypothesis where n_params is the number of parameters in the (unconstrained) model. See details for more information.
`c`	a length k vector specifying part of the null hypothesis. See details for more information.
`h`	difference used to approximate the derivatives.
`x`	object of class `'wald'` generated by the function `Wald_test`.
`...`	other arguments passed to `fn`
`digits`	how many significant digits to print?

Details

Denoting the true parameter value by θ_0, we test the null hypothesis $A\theta_0 = c$. Under the null, the test statistic is asymptotically χ^2-distributed with k (`=nrow(A)`) degrees of freedom. The parameter θ_0 is assumed to have the same form as in the model supplied in the argument `gmvar` and it is presented in the documentation of the argument `params` in the function `GMVAR` (see `?GMVAR`).

Finally, note that this function does **not** check whether the specified constraints are feasible (e.g. whether the implied constrained model would be stationary or have positive definite error term covariance matrices).

Value

Returns an object of class $'wald'$ containing the test statistic and the related p-value.

Methods (by generic)

- `print`: print method

References

- Kalliovirta L., Meitz M. and Saikkonen P. 2016. Gaussian mixture vector autoregression. *Journal of Econometrics*, **192**, 485-498.
- Virolainen S. 2020. Structural Gaussian mixture vector autoregressive model. Unpublished working paper, available as arXiv:2007.04713.

See Also

LR_test, fitGMVAR, GMVAR, diagnostic_plot, profile_logliks, quantile_residual_tests, cond_moment_plot

Examples

```
# Load the data
data(eurusd, package="gmvarkit")
data <- cbind(10*eurusd[,1], 100*eurusd[,2])
colnames(data) <- colnames(eurusd)

# Structural GMVAR(2, 2), d=2 model identified with sign-constraints:
W_222 <- matrix(c(1, NA, -1, 1), nrow=2, byrow=FALSE)
fit222s <- fitGMVAR(data, p=2, M=2, structural_pars=list(W=W_222),
                    ncalls=1, seeds=1)
fit222s

# Test whether the lambda parameters (of the second regime) are identical:
# fit222s has parameter vector of length 27 with the lambda parameters
# in elements 25 and 26.
A <- matrix(c(rep(0, times=24), 1, -1, 0), nrow=1, ncol=27)
c <- 0
Wald_test(fit222s, A, c)

# Test whether the off-diagonal elements of the first regime's first
# AR coefficient matrix (A_11) are both zero:
# fit222s has parameter vector of length 27 and the off-diagonal elements
# of the 1st regime's 1st AR coefficient matrix are in the elements 6 and 7.
A <- rbind(c(rep(0, times=5), 1, rep(0, times=21)),
           c(rep(0, times=6), 1, rep(0, times=20)))
c <- c(0, 0)
Wald_test(fit222s, A, c)
```

Wvec *Vectorization operator that removes zeros*

Description

Wvec stacks columns of the given matrix to form a vector and removes elements that are zeros.

Usage

```
Wvec(W)
```

Arguments

`W`	a size (dxd) square matrix to be vectorized.

Value

a vector of length $d^2 - n_zeros$ where n_zeros is the number of zero entries in the matrix `W`.

Warning

No argument checks!

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