Package ‘graphicalVAR’

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Estimate the graphical VAR model.

**Description**

Estimates the graphical VAR (Wild et al., 2010) model through LASSO estimation coupled with extended Bayesian information criterion for choosing the optimal tuning parameters. The estimation procedure is outlined by Rothman, Levina and Zhu (2010) and is further described by Abegaz and Wit (2013). The procedure here is based on the work done in the R package SparseTSCGM (Abegaz and Wit, 2014).

**Usage**

```r
graphicalVAR(data, nLambda = 50, verbose = TRUE, gamma = 0.5, scale = TRUE, lambda_beta, lambda_kappa, maxit.in = 100, maxit.out = 100, deleteMissings = TRUE, penalize.diagonal = TRUE, lambda_min_kappa = 0.05, lambda_min_beta = lambda_min_kappa, mimic = c("current", "0.1.2", "0.1.4", "0.1.5", "0.2"), vars, beepvar, dayvar, idvar, lags = 1, centerWithin = TRUE, likelihood = c("unpenalized", "penalized"))
```

**Arguments**

- **data**: A matrix or data frame containing repeated measures (rows) on a set of variables (columns). Must not contain missing data.
- **nLambda**: The number of both lambda parameters to test. Defaults to 50, which results in 2500 models to evaluate.
- **verbose**: Logical, should a progress bar be printed to the console?
- **gamma**: The EBIC hyper-parameter. Set to 0 to use regular BIC.
- **scale**: Logical, should responses be standardized before estimation?
- **lambda_beta**: An optional vector of lambda_beta values to test. Set lambda_beta = 0 argument and lambda_kappa = 0 for unregularized estimation.
- **lambda_kappa**: An optional vector of lambda_kappa values to test. Set lambda_beta = 0 argument and lambda_kappa = 0 for unregularized estimation.
- **maxit.in**: Maximum number of iterations in the inner loop (computing beta)
- **maxit.out**: Maximum number of iterations in the outer loop
- **deleteMissings**: Logical, should missing responses be deleted?
- **penalize.diagonal**: Logical, should the diagonal of beta be penalized (i.e., penalize auto-regressions)?
- **lambda_min_kappa**: Multiplier of maximal tuning parameter for kappa
- **lambda_min_beta**: Multiplier of maximal tuning parameter for beta
mimic Allows one to mimic earlier versions of graphicalVAR
vars Vectors of variables to include in the analysis
beepvar String indicating assessment beep per day (if missing, is added). Adding this argument will cause non-consecutive beeps to be treated as missing!
dayvar String indicating assessment day. Adding this argument makes sure that the first measurement of a day is not regressed on the last measurement of the previous day. IMPORTANT: only add this if the data has multiple observations per day.
idvar String indicating the subject ID
lags Vector of lags to include
centerWithin Logical, should subject data be within-person centered before estimating fixed effects?
likelihood Should likelihood be computed based on penalized contemporaneous matrix or unpenalized contemporaneous matrix. Set to "penalized" to mimic version 2.5 and later of sparseTSCGM.

Details
Let $y_{t}$ denote the vector of centered responses of a subject on a set of items on time point $t$. The graphical VAR model, using only one lag, is defined as follows:

$$y_{t} = Beta \cdot y_{y-1} + \epsilon_{t}$$

In which $\epsilon_{t}$ is a vector of error and is independent between time points but not within time points. Within time points, the error is normally distributed with mean vector $0$ and precision matrix (inverse covariance matrix) $Kappa$. The $Beta$ matrix encodes the between time point interactions and the $Kappa$ matrix encodes the within time point interactions. We aim to find a sparse solution for both $Beta$ and $Kappa$, and do so by applying the LASSO algorithm as detailed by Rothman, Levina and Zhu (2010). The LASSO algorithm uses two tuning parameters, $lambda_{beta}$ controlling the sparsity in $Beta$ and $lambda_{kappa}$ controlling the sparsity in $Kappa$. We estimate the model under a (by default) 50 by 50 grid of tuning parameters and choose the tuning parameters that optimize the extended Bayesian Information Criterion (EBIC; Chen and Chen, 2008).

After estimation, the $Beta$ and $Kappa$ matrices can be standardized as described by Wild et al. (2010). The $Kappa$ matrix can be standardized to partial contemporaneous correlations (PCC) as follows:

$$PCC(y_{i,t}, y_{j,t}) = -kappa_{ij} / (\text{sqrt}kappa_{ii} \text{ kappa}_{jj})$$

Similarly, the $Beta$ matrix can be standardized to partial directed correlations (PDC):

$$PDC(y_{i,t-1}, y_{j,t}) = beta_{ji} / \text{sqrt}\sigma_{jj} \text{ kappa}_{ii} + beta_{ji}{^2}$$

In which $\sigma$ is the inverse of $kappa$. Note that this process transposes the $Beta$ matrix. This is done because in representing a directed network it is typical to let rows indicate the node of origin and columns the node of destination.

Set $lambda_{beta} = 0$ argument and $lambda_{kappa} = 0$ for unregularized estimation.

Value
A graphicalVAR object, which is a list containing:

PCC The partial contemporaneous correlation network
PDC  The partial directed correlation network
beta  The estimated beta matrix
kappa The estimated kappa matrix
EBIC The optimal EBIC
path Results of all tested tuning parameters
labels A vector containing the node labels

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References
Fentaw Abegaz and Ernst Wit (2013). Sparse time series chain graphical models for reconstructing
vector autoregressive modelling approach to the analysis of electronic diary data. BMC medical
research methodology, 10(1), 28.

Examples
# Simulate model:
Mod <- randomGVARmodel(4, probKappaEdge = 0.8, probBetaEdge = 0.8)

# Simulate data:
Data <- graphicalVARsim(100, Mod$beta, Mod$kappa)

# Estimate model:
Res <- graphicalVAR(Data, gamma = 0, nLambda = 10)

# Plot results:
layout(t(1:2))
plot(Mod, "PCC", layout = "circle")
plot(Res, "PCC", layout = "circle")
plot(Mod, "PDC", layout = "circle")
plot(Res, "PDC", layout = "circle")
graphicalVARsim

Simulates data from the graphical VAR model

Description

Simulates data from the graphical VAR model, see graphicalVAR for details.

Usage

graphicalVARsim(nTime, beta, kappa, mean = rep(0, ncol(kappa)), init =
         mean, warmup = 100, lbound = rep(-Inf, ncol(kappa)),
         ubound = rep(Inf, ncol(kappa)))

Arguments

nTime Number of time points to sample
beta The Beta matrix to use
kappa The Kappa matrix to use
mean Means to use
init Initial values
warmup The amount of samples to use as warmup (not returned)
lbound Lower bound, at every time point values below this bound are set to the bound.
ubound Upper bound, at every time point values above this bound are set to the bound.

Value

A matrix containing the simulated data.

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mlGraphicalVAR

Pooled and individual graphical VAR estimation

Description

This function fits fixed effect temporal and contemporaneous networks over multiple subjects and runs separate graphical VAR models per subject. The algorithm does: (1) pool all data, within-subject center variables and run graphicalVAR to obtain fixed effects, (2) run EBICglasso on subject means to obtain a between-subjects network, (3) run graphicalVAR on data of every subject to obtain individual networks. See arxiv.org/abs/1609.04156 for more details.
Usage

```
mlGraphicalVAR(data, vars, beepvar, dayvar, idvar, scale = TRUE,
               centerWithin = TRUE, gamma = 0.5, verbose = TRUE,
               subjectNetworks = TRUE, lambda_min_kappa_fixed = 0.001,
               lambda_min_beta_fixed = 0.001, lambda_min_kappa = 0.05,
               lambda_min_beta = lambda_min_kappa, lambda_min_glasso = 0.01,
               ...
```

Arguments

- **data**: Data frame
- **vars**: Vectors of variables to include in the analysis
- **beepvar**: String indicating assessment beep per day (if missing, is added). Adding this argument will cause non-consecutive beeps to be treated as missing!
- **dayvar**: String indicating assessment day. Adding this argument makes sure that the first measurement of a day is not regressed on the last measurement of the previous day. IMPORTANT: only add this if the data has multiple observations per day.
- **idvar**: String indicating the subject ID
- **scale**: Logical, should variables be standardized before estimation?
- **centerWithin**: Logical, should subject data be within-person centered before estimating fixed effects?
- **gamma**: EBIC tuning parameter.
- **verbose**: Logical indicating if console messages and the progress bar should be shown.
- **subjectNetworks**: TRUE to estimate all subject numbers, or a vector with IDs of which subject numbers should be estimated.
- **lambda_min_kappa_fixed**: Multiplier of maximal tuning parameter
- **lambda_min_beta_fixed**: Multiplier of maximal tuning parameter
- **lambda_min_kappa**: Multiplier of maximal tuning parameter
- **lambda_min_beta**: Multiplier of maximal tuning parameter
- **lambda_min_glasso**: Multiplier of maximal tuning parameter
- ... Arguments sent to `graphicalVAR`

Value

A "mlGraphicalVAR" object with the following elements:

- **fixedPCC**: Estimated fixed effects (partial contemporaneous correlations) of contemporaneous effects
- **fixedPDC**: Estimated fixed effects (partial directed correlations) of temporal effects
mlGraphicalVAR

fixedResults Full object of pooled data estimation (fixed effects)
betweenNet Estimated between-subjects network (partial correlations)
ids Vector of subject IDs
subjectPCC List of estimated individual contemporaneous networks
subjectPDC List of estimated individual directed networks
subjecResults List of full results of individual estimations

Author(s)
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References
Epskamp, S., Waldorp, L. J., M\~ottus, R., & Borsboom, D. Discovering Psychological Dynamics: The Gaussian Graphical Model in Cross-sectional and Time-series Data.

See Also
graphicalVAR

Examples

## Not run:
# Simulate data:
Sim <- simMLgvar(nTime = 50, nPerson = 20, nVar = 3)

# Estimate model:
Res <- mlGraphicalVAR(Sim$data, vars = Sim$vars, idvar = Sim$idvar)

layout(t(1:2))
library("qgraph")

# Temporal fixed effects
qugraph(Res$fixedPDC, title = "Estimated fixed PDC", layout = "circle")
qugraph(Sim$fixedPDC, title = "Simulated fixed PDC", layout = "circle")

# Contemporaneous fixed effects
qugraph(Res$fixedPCC, title = "Estimated fixed PCC", layout = "circle")
qugraph(Sim$fixedPCC, title = "Simulated fixed PCC", layout = "circle")

## End(Not run)
### plot.graphicalVAR

**Plot method for graphicalVAR objects**

**Description**

Sends the estimated PCC and PDC networks to `qgraph`.

**Usage**

```r
## S3 method for class 'graphicalVAR'
plot(x, include = c("PCC", "PDC"), repulsion = 1,
     horizontal = TRUE, titles = TRUE, sameLayout = TRUE,
     unweightedLayout = FALSE, ...)
```

**Arguments**

- `x` A graphicalVAR object
- `include` A vector of at most two containing "PCC" and "PDC" indicating which networks should be plotted and in what order.
- `repulsion` The repulsion argument used in `qgraph`
- `horizontal` Logical, should the networks be plotted horizontal or vertical?
- `titles` Logical, should titles be added to the plots?
- `sameLayout` Logical, should both networks be plotted in the same layout?
- `unweightedLayout` Logical, should the layout be based on the unweighted network instead of the weighted network?
- `...` Arguments sent to `qgraph`

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### print.graphicalVAR

**S3 methods for graphicalVAR objects.**

**Description**

Prints a short overview of the results of `graphicalVAR`.

**Usage**

```r
## S3 method for class 'graphicalVAR'
print(x, ...)  
## S3 method for class 'graphicalVAR'
summary(object, ...)
```
**randomGVARmodel**

**Arguments**

- `x`: A graphicalVAR object
- `object`: A graphicalVAR object
- `...`: Not used.

**Author(s)**

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**randomGVARmodel**  
*Simulate a graphical VAR model*

**Description**

Simulates an contemporaneous and temporal network using the method described by Yin and Li (2001)

**Usage**

```r
randomGVARmodel(Nvar, probKappaEdge = 0.1, probKappaPositive = 0.5, probBetaEdge = 0.1,  
                 probBetaPositive = 0.5, maxtry = 10, kappaConstant = 1.1)
```

**Arguments**

- `Nvar`: Number of variables
- `probKappaEdge`: Probability of an edge in contemporaneous network
- `probKappaPositive`: Proportion of positive edges in contemporaneous network
- `probBetaEdge`: Probability of an edge in temporal network
- `probBetaPositive`: Propotion of positive edges in temporal network
- `maxtry`: Maximum number of attempts to create a stationairy VAR model
- `kappaConstant`: The constant used in making kappa positive definite. See Yin and Li (2001)

**Details**

The resulting simulated networks can be plotted using the plot method.

**Value**

A list containing:

- `kappa`: True kappa structure (residual inverse variance-covariance matrix)
- `beta`: True beta structure
- `PCC`: True partial contemporaneous correlations
- `PDC`: True partial temporal correlations
**Author(s)**
Sacha Epskamp

**References**

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**Generate graphical VAR data of multiple subjects**

**Description**
See arxiv.org/abs/1609.04156 for details.

**Usage**

```r
simMLgvar(ntimeL, nvarL, npersonL, proppositive = .5, kappaRange = c(0.25, 0.5),
          betarange = c(0.25, 0.5), betweenRange = c(0.25, 0.5),
          rewireWithin = 0, betweenVar = 1, withinVar = 0.25,
          temporalOffset = 2)
```

**Arguments**
- `ntime` Number of time points per subject
- `nvar` Number of variables
- `nperson` Number of subjects
- `proppositive` Proportion of positive edges
- `kappaRange` Range of partial contemporaneous correlation coefficients
- `betarange` Range of temporal coefficients
- `betweenRange` Range of partial between-subjects coefficients
- `rewireWithin` Rewiring probability of contemporaneous networks
- `betweenVar` Between-subjects variabce
- `withinVar` Contemporaneous variance
- `temporalOffset` Specifies the temporal network. Setting this to 2 connects $X_i$ to $X_{i+2}$

**Value**
A "simMLgvar" object with the following elements:
- `data` Generated dataset
- `fixedKappa` Fixed inverse contemporaneous covariance matrix
- `fixedPCC` Fixed contemporaneous partial correlation network
**simML.gvar**

- `fixedBeta`  Fixed temporal network
- `fixedPDC`  Fixed standardized temporal network
- `between` Fixed between-subjects network
- `means` True means
- `personData` Dataset split per person
- `idvar` String indicating the id variable
- `vars` Vector of strings indicating the variables

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