

Package ‘graphicalVAR’

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Type Package

Title Graphical VAR for Experience Sampling Data

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Description Estimates within and between time point interactions in experience sampling data, using the Graphical vector autoregression model in combination with regularization. See also Epskamp, Waldorp, Mottus & Borsboom (2018) <[doi:10.1080/00273171.2018.1454823](https://doi.org/10.1080/00273171.2018.1454823)>.

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LinkingTo Rcpp, RcppArmadillo

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graphicalVAR

*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

```
graphicalVAR(data, nLambda = 50, verbose = TRUE, gamma = 0.5, scale
              = TRUE, lambda_beta, lambda_kappa,
              regularize_mat_beta, regularize_mat_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", "0.3.2", "0.1.2", "0.1.4", "0.1.5",
              "0.2"), vars, beepvar, dayvar, idvar, lags = 1,
              centerWithin = TRUE, likelihood = c("unpenalized",
              "penalized"), ebic_tol = 1e-04)
```

Arguments

data	A matrix or data frame containing repeated measures (rows) on a set of variables (columns).
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.
regularize_mat_beta	A logical matrix indicating which elements of the beta matrix should be regularized (experimental).
regularize_mat_kappa	A logical matrix indicating which elements of the kappa matrix should be regularized (experimental).
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.
ebic_tol	Tolerance used to judge if two EBIC values are the same. If two values are deemed the same the model with the lowest tuning parameter (kappa preferred) will be selected.

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:

$$y[t] = \text{Beta } y[t-1] + \text{epsilon}[t]$$

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, λ_{beta} controlling the sparsity in Beta and λ_{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:

$$\text{PCC}(y[i,t], y[j,t]) = -\text{kappa}[ij] / \sqrt{(\text{kappa}[ii] \text{kappa}[jj])}$$

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

$$\text{PDC}(y[i,t-1], y[j,t]) = \text{beta}[ji] / \sqrt{(\text{sigma}[jj] \text{kappa}[ii] + \text{beta}[ji]^2)}$$

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.

Missing data are removed listwise after augmenting the dataset. This means that if there is a missing response at time t, the row corresponding to time t-1 and time t and the row corresponding to time t and time t+1 are removed.

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

Author(s)

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References

- Chen, J., & Chen, Z. (2008). Extended Bayesian information criteria for model selection with large model spaces. *Biometrika*, 95(3), 759-771.
- Fentaw Abegaz and Ernst Wit (2013). Sparse time series chain graphical models for reconstructing genetic networks. *Biostatistics*. 14, 3: 586-599.
- Fentaw Abegaz and Ernst Wit (2014). SparseTSCGM: Sparse time series chain graphical models. R package version 2.1.1. <http://CRAN.R-project.org/package=SparseTSCGM>
- Rothman, A.J., Levina, E., and Zhu, J. (2010). Sparse multivariate regression with covariance estimation. *Journal of Computational and Graphical Statistics*. 19: 947-962.
- Wild, B., Eichler, M., Friederich, H. C., Hartmann, M., Zipfel, S., & Herzog, W. (2010). A graphical 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 = 5)

## Not run:
# For more precision, run:
Res <- graphicalVAR(Data, gamma = 0)

# 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")

## End(Not run)
```

graphicalVARsim	<i>Simulates data from the graphical VAR model</i>
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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

<code>data</code>	Data frame
<code>vars</code>	Vectors of variables to include in the analysis
<code>beepvar</code>	String indicating assessment beep per day (if missing, is added). Adding this argument will cause non-consecutive beeps to be treated as missing!
<code>dayvar</code>	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.
<code>idvar</code>	String indicating the subject ID
<code>scale</code>	Logical, should variables be standardized before estimation?
<code>centerWithin</code>	Logical, should subject data be within-person centered before estimating fixed effects?
<code>gamma</code>	EBIC tuning parameter.
<code>verbose</code>	Logical indicating if console messages and the progress bar should be shown.
<code>subjectNetworks</code>	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
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
subjectResults	List of full results of individual estimations

Author(s)

Sacha Epskamp <mail@sachaepskamp.com>

References

Epskamp, S., Waldorp, L. J., Mottus, 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
qgraph(Res$fixedPDC, title = "Estimated fixed PDC", layout = "circle")
qgraph(Sim$fixedPDC, title = "Simulated fixed PDC", layout = "circle")

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

## End(Not run)

```

plot.graphicalVAR	<i>Plot method for graphicalVAR objects</i>
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Description

Sends the estimated PCC and PDC networks to [qgraph](#).

Usage

```

## 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

Author(s)

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print.graphicalVAR *S3 methods for graphicalVAR objects.*

Description

Prints a short overview of the results of [graphicalVAR](#)

Usage

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

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

```
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	Proportion of positive edges in temporal network
maxtry	Maximum number of attempts to create a stationary 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

Yin, J., & Li, H. (2011). A sparse conditional gaussian graphical model for analysis of genetical genomics data. *The annals of applied statistics*, 5(4), 2630-2650.

simMLgvar

Generate graphical VAR data of multiple subjects

Description

See arxiv.org/abs/1609.04156 for details.

Usage

```
simMLgvar(nTime, nVar, nPerson, propPositive = 0.5, kappaRange = c(0.25, 0.5),
  betaRange = c(0.25, 0.5), betweenRange = c(0.25, 0.5),
  rewiringWithin = 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 variance
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
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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