Package 'graphicalVAR'

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Type Package

Title Graphical VAR for Experience Sampling Data

Version 0.3.4

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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>.

LinkingTo Rcpp, RcppArmadillo

Imports Rcpp (>= 0.11.3), Matrix, glasso, glmnet, mvtnorm, qgraph (>= 1.3.1), dplyr, methods, igraph, rlang

Depends R (>= 3.1.0)

NeedsCompilation yes

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R topics documented:

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] = Beta 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] / sqrt(kappa[ii] kappa[jj])

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

PDC(y[i,t-1], y[j,t]) = beta[ji] / sqrt(sigma[jj] 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.

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` *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.

Author(s)

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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
`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., 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` *Plot method for graphicalVAR objects*

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
: 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

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.

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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),
          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
`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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Index