Package ‘psychNET’

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Type Package

Title Psychometric Networks for Intensive Longitudinal Data

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Description

Depends R (>= 3.5)

Imports vars, igraph, imputeTS, Hmisc, SparseTSCGM, mlVAR, qgraph, graphicalVAR, bigtime,mvm, crayon, longitudinal, networktools,
Description

This package has been designed in order to provide various psychometric network modelling techniques for multivariate time series data from the behavioral domain, in a simple wrapper function. The aim is to estimate the temporal and contemporaneous interaction structure in a (possibly) sparse fashion and thereby being able to visualize these interactions by means of conditional independence graphs. Depending on the model, the interactions are estimated at the individual level – intra-individual dynamics – or population level – inter-individual dynamics.
Details

In the last decade, time series data became popular in the behavioral sciences. These data, allow us to study the dynamics of complex behavioral systems both at the individual and the population level. Vector autoregression (VAR) is the cornerstone in the statistical modelling of multivariate time series data and various VAR extensions are available that can handle cases where additional complexities are imposed in the analysis.

This package introduces the main psychNET function that is used to fit various dynamic models. Models that can be fitted to time-series data from one person using the psychNET function are:

- **Vector Autoregressive (VAR) models**: Traditional VAR model or VAR model with exogenous variables (VARX). See the help file from the VAR() function from the R package vars for more details.
- **Sparse Vector Autoregressive (SVAR) models**: SVAR model estimated using penalized multivariate least squares (see fitVAR function in the R package sparsevar). SVARs estimated using penalized least squares with simultaneous lag estimation (SVARHL) and exogenous variables (SVARHLX) implemented in the functions sparseVAR and sparseVARX respectively from the R package bigtime. SVAR model with simultaneous covariance estimation using penalized likelihood approach known as graphical VAR (GVAR) implemented in the function graphicalVAR from the package graphicalVAR. A SVAR model for mixed type of time series with marginal distributions in the exponential family (SMVAR), implemented in the function mvar from the R package mgm.
- **Sparse Vector Error Correction Model (SVECM)**: SVECM estimated using penalized multivariate least squares that is implemented in the function fitVECM from the R package sparsevar.
- **Sparse Vector Autoregressive Moving Average (SVARMA) model**: SVARMA model where the parameters are estimated using penalized least squares with simultaneous lag estimation (SVARMAHL) implemented in the function sparseVARMA from the R package bigtime.
- **Sparse Time-Varying Vector Autoregressive (TV-SVAR) model**: TV-SVAR model where the parameters are allowed to vary smoothly with time. This model can handle time series with marginal distributions in the exponential family. The model is implemented in the function tvmvar, which is available with the R package mgm. (This model is NOT yet available in the psychNET package. To be expected with the next update.)
- **Dynamic factor model (DFM)**: DFM with three different types of estimates for the latent series. For details you can check the function dfm from the R package dynfactoR available at github.

For network inference at the population level from nested time-series data, two models in the broad class of VAR models can be fitted via the psychNET function. These are:

- **Multilevel Vector Autoregressive (MLVAR) model**: This model estimates group as well as individual level effects and it is implemented in the R function mlVAR from the R package mlVAR.
- **Sparse Vector Autoregressive (SVAR) model**: This model estimates sparse group level networks from nested time series with simultaneous covariance estimation. We call this model group graphical VAR (GGVAR) and it has been primarily implemented in the function sparse.tscgm available with R package SparseTSCGM.
Author(s)

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References


Examples

# Load the R package psychNET
library(psychNET)

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MIR  

Multivariate symptom time series from the Mapping Individual Routes Of Risk and Resilience (MIORR) study.

Description

The sample comprises 51 individuals of 18-35 years from two subsamples (n1=25 and n2=26 respectively). Each subgroup, has an increasingly more severe psychopathological level and thus representing subsequent clinical stages.

Usage

data("MIR")
Format

A data frame with 4488 observations on the following 36 variables.

ID : An integer vector with identification numbers for each participant.
GROUP : An integer vector with identification numbers for each subgroup of participants.
TIME : An integer vector with the time point when each measurement has been taken.
relx : numeric. "I felt relaxed today." [0,100]
calm : numeric. "I felt calm today." [0,100]
satf : numeric. "I felt satisfied today." [0,100]
ever : numeric. "I felt energetic today." [0,100]
enth : numeric. "I felt enthousiastic today." [0,100]
chrf : numeric. "I felt cheerful today." [0,100]
apat : numeric. "I felt apathetic today." [0,100]
tire : numeric. "I felt tired today." [0,100]
down : numeric. "I felt down today." [0,100]
anxi : numeric. "I felt anxious today." [0,100]
rstl : numeric. "I felt restless today." [0,100]
irtb : numeric. "I felt irritable today." [0,100]
irtt : numeric. "I felt irritated today." [0,100]
talk : numeric. "I felt talkative today." [0,100]
conf : numeric. "I felt confident today." [0,100]
empt : numeric. "I felt empty today." [0,100]
worr : numeric. "I felt worried today." [0,100]
susp : numeric. "I felt suspicious today." [0,100]
incm : numeric. "Today I had the feeling of falling short." [0,100]
hand : numeric. "Today I could handle what came my way." [0,100]
conc : numeric. "I could concentrate well today." [0,100]
life : numeric. "I found my life was worthwhile today." [0,100]
phys : numeric. "I was bothered by physical symptoms today." [0,100]
unrs : numeric. "Today I had the tendency to do something wild." [0,100]
thal : numeric. "My thoughts wouldn’t leave me alone today." [0,100]
thr : numeric. "My thoughts were racing today." [0,100]
the : numeric. "My thoughts were difficult to express today." [0,100]
ornl : numeric. "Today I had the feeling that others did not like me." [0,100]
octr : numeric. "I felt that others could read my thoughts today." [0,100]
unrl : numeric. "I felt unreal today." [0,100]
cont : numeric. "I felt that other could control me today." [0,100]
enjy : numeric. "I could experience pleasure when nice things happened today." [0,100]
undt : numeric. "I felt like undertaking something today." [0,100]
References


Examples

```r
data(MIR)
str(MIR)
```

---

**MOOVD**

*Multivariate symptom time series from an individual in the Mood and Movement in Daily life (MOOVD) study.*

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Description

Discrete valued multivariate symptom time series from a depressed individual in the MOOVD study. The responses of the participant are recorded for 30 days, three times per day (one vector of responses obtained at each beep).

Usage

```r
data("MOOVD")
```

Format

A data frame with 90 incomplete observations on the following 30 variables.

- **Appetite**: ordered factor. "My apetite is..." [-3,3]
- **Psychomotor retardation**: ordered factor. "My movements are..." [-3,3]
- **Interest**: ordered factor. "My interest in the things around me is..." [-3,3]
- **Talkative**: ordered factor. "I feel talkative" [1,7]
- **Energetic**: ordered factor. "I feel energetic..." [1,7]
- **Tense**: ordered factor. "I feel tense..." [1,7]
- **Anxious**: ordered factor. "I feel anxious..." [1,7]
- **Enthusiastic**: ordered factor. "I feel enthousiastic..." [1,7]
- **Self assured**: ordered factor. "I feel self assured..." [1,7]
- **Distracted**: ordered factor. "I feel self distracted..." [1,7]
- **Restless**: ordered factor. "I feel self restless..." [1,7]
- **Irritated**: ordered factor. "I feel self irritated..." [1,7]
- **Content**: ordered factor. "I feel content..." [1,7]
- **Happy**: ordered factor. "I feel cheerful..." [1,7]
Sad : ordered factor. "I feel sad..." [1,7]
Cheerful : ordered factor. "I feel excited..." [1,7]
Guilty : ordered factor. "I feel guilty..." [1,7]
Defeated : ordered factor. "I feel defeated..." [1,7]
Tired : ordered factor. "I feel tired..." [1,7]
Relaxed : ordered factor. "I feel relaxed..." [1,7]
Hopeless : ordered factor. "I feel hopeless..." [1,7]
Appreciated : ordered factor. "I feel appreciated..." [1,7]
Thoughts about death : ordered factor. "I think about death a lot..." [1,7]
Can handle what comes my way : ordered factor. "I can handle what comes my way..." [1,7]
Rumination : ordered factor. "I worry a lot..." [1,7]
Negative thoughts : ordered factor. "Many negative thoughts go through my mind..." [1,7]
Concentrate : ordered factor. "I am able to concentrate very well..." [1,7]
Slowed thoughts : ordered factor. "My thoughts are slow..." [1,7]
DAY : numeric. Day variable
BEEP : integer. Beep variable

References


Examples

data(MOOVD)
str(MOOVD)

plot.pnt

Plot method for S3 class "pnt" objects.

Description

Generic that plots an object of class "pnt".

Usage

## S3 method for class 'pnt'
plot(x, type, person, community, ...)

Arguments

**x**
- An object resulted from the `psychNET` function.

**type**
- String argument, which controls the type of plot that will be returned. The available options are: "temporal" (for temporal network), "contemporaneous" (for contemporaneous network), "between" (for between subjects network), and "both" (both temporal and contemporaneous networks)

**person**
- This can be a single number or vector of numbers that denotes the person index for which plots will be returned. This argument is used only when the model fitted is a Multi-level VAR (i.e. the argument `model` in the `psychNET` function equals to "MLVAR").

**community**
- Logical argument. When `TRUE`, the function fits a spinglass community detection algorithm with negative weights where only the present edges are taken into account. **WARNING!!** this can make the `plot.pnt` function to be very slow.

... 
- Other arguments to be passed on to the `plot.igraph` function. Use this with care since some arguments in are already specified internally.

Details

For This function is used to visualize networks estimated via the `psychNET` function. See additional details of the function `psychNET`.

Value

The value returned by the plot is a list where its elements are two lists named temporal and contemporaneous respectively. These lists contain objects of class `igraph` and `qgraph` that can be used by the user to create tailor made plots.

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References


Generic print function that is used to print information to the console for the function call, the time elapsed, the data used, the fitted model and the model estimates.

Arguments

- `x`: is an object resulted from the psychNET function
- `...`: Not used

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References


See Also

psychNET
psychNET

Psychometric networks estimated by multivariate time series methods.

Description

Wrapper function of multivariate time-series models, which can be used to obtain symptom networks (i.e., networks of symptom-symptom interactions).

Usage

psychNET(data, model, lag, criterion, nFact, penalty, lambda1, lambda2, covariates, impute, transform, ...)

Arguments

data : Usually a "matrix", "data.frame", or "longitudinal" object of dimension \((n*T) \times p\) where \(n\) is the number of individuals. For time-series data from multiple persons, an additional numeric column explicitly named "ID" indicating from which person the measurements are coming from should be included in the data. Additionally, with experience sampling data that are nested within days, additional columns named "DAY" and "BEEP" can be included in data from which we calculate the consecutiveness of the measurements. Alternatively, a column named "TIME" denoting the measurement consecutiveness can be provided in data. See details.

model : This argument controls the model to be fitted to the data. The available options are: "VAR", "SVAR", "SMVAR", "SVECM", "GVAR", "SVARHL", "SVARHLX", "SVARHLMA", "DFM", "MLVAR", "GGVAR".

lag : Specifies the lag order of the process. When model is "DFM" lag corresponds to the order of the factor process. When model is "SVARHL", "SVARHLX", or "SVARHLMA" lag can be NULL and the model chooses the optimal lag via regularized hierarchical lag structures.

criterion : The information criterion to be used in order to tune the penalty parameters of regularized (sparse) VAR models. Available options are: "CV", "AIC", "BIC", "EBIC", "GIC", and "MBIC". This argument depends on the model argument (see details).

nFact : This argument is used only when model="DFM" and controls the number of the static factors in the dynamic factor model.

penalty : This argument controls the type of regularization to be used and depends on the model argument (see details). Available options are "LASSO", "ENET", "SCAD", "MCP", and "HLag".

lambda1 : A numeric vector with length greater than one that specifies the values of the penalty parameter for regularized VARs. Typically, this corresponds to the penalty parameter for the lagged effects. When model is "GVAR" or "GGVAR" then lambda1 is used as the penalty value for the precision matrix.
lambda2: A numeric vector with length greater than one. This argument is used only when model is "GVAR" or "GGVAR" and controls the value of the penalty parameter for the lagged effects.

covariates: This argument is used only when model is "VAR" or "SVARXL" in order to specify covariates for VARX or SVARX models.

impute: String that is used to specify the imputation method when missing values exist in the data or when missing values are inserted to transform non-equidistant measurements into equidistant. It can be a single string or a vector of strings with length equal to the number of symptoms in the data. In the latter case, each symptom can be imputed using an explicit method. Available options are: "Kalman.arima", "Kalman.struct", "Interpol.linear", "Interpol.spline", "Interpol.stine", "LOCF", "NOCB", "MA.simple", "MA.linear", "MA.exponent", "mean", "mode", "median", "random", "Season.int.linear", "Season.int.spline", "Season.int.stine", "Season.LOCF", "Season.NOCB", "Season.mean", "Season.median", "Season.mode", "Season.MA", "Season.kalman", "Season.random".

transform: String that is used to specify the transformation function. It can be a single string or a vector of strings with length equal to the number of symptoms in the data. In the latter case, each symptom can be transformed using an explicit function. Available options are: "log", "log10", "Copula_discr", "Copula_skew", "Zero.mean", "Standardize", "Power", "Logit", "Square.root", "Power2", "Power3", "Cube.root".

Details

The data

The data to be used in the psychNET function must strictly contain symptom expression data where the measurements are ordered by time. The only additional variables that are allowed in the data except symptom expression are a variable explicitly coded as "ID" when multiple persons need to be analyzed together, a variable coded as "DAY" when multiple measurements per day are taken and a variable called "BEEP" to indicate the measurement intensity within a given day. The variables "DAY" and "BEEP" are used internally to construct a time variable that denotes the consecutive-ness of the measurements. The time variable can also be provided in the data explicitly named as "TIME". The only models in the package that can handle non-equidistant observations naturally are the "GVAR", "SMVAR", and "MLVAR". In any other model, non-equidistant measurements first are transformed to equidistant by inserting missing values, which are then imputed using the imputation method specified in the impute argument.

The models

Here we provide some more details with respect to the models implemented in the package.

VAR model (VAR)

The traditional VAR model is fitted with the psychNET function by setting model="VAR". This model is originally implemented in the function VAR that comes with the R package vars. In this implementation the unknown model parameters are estimated by ordinary least squares (OLS) per equation. The arguments lag and covariates of the psychNET function correspond to the parameter p and exogen respectively of the original VAR function. Other parameters that are used
in the original function can be passed through the ... structure (technically known as ellipsis). For details on arguments that can be passed to the three dots when fitting a VAR the user can type \texttt{?vars::VAR} into the console in order to access its help file.

**Sparse VAR model (SVAR)**

A sparse VAR model is fitted with the \texttt{psychNET} function by setting \texttt{model=“SVAR”}. This model is implemented in the function \texttt{fitVAR} from the R package \texttt{sparsevar} and the unknown model parameters are estimated via penalized multivariate least squares. Three different types of penalization are available that can be passed to the function through the \texttt{penalty} argument. If you set \texttt{penalty=“ENET”} an elasticnet penalty is applied to the parameters with other option being ”SCAD” for SCAD type of penalization and ”MCP” for MC+ penalty. The only option available for tuning the penalty parameter is k-fold cross validation. The parameter \texttt{lag} of the \texttt{psychNET} function corresponds to the parameter \texttt{p} of the \texttt{fitVAR} function, the parameter \texttt{penalty} is used in the same way as in the \texttt{fitVAR} function while \texttt{criterion} substitutes the argument \texttt{method} of the \texttt{fitVAR} function. Additional arguments can be passed to the \texttt{fitVAR} function by using the ... structure of the \texttt{psychNET} function. For details on the original function and additional parameters that can be used you can look at \texttt{?sparsevar::fitVAR}.

**Sparse VAR model with hierarchical lag structures and additional covariates (SVARHL and SVARHLX)**

A sparse VAR that offers the possibility of simultaneous lag estimation is fitted by setting \texttt{model=“SVARHL”}. Additional covariates can be used by setting \texttt{model=“SVARHLX”} and providing the covariates data to the argument \texttt{covariates} of the \texttt{psychNET} function. These two models are available with the R package \texttt{bigtime} in the functions \texttt{sparseVAR} and \texttt{sparseVARX} respectively. These models are estimated by penalized least squares optimized by a proximal gradient algorithm. These models offer two types of penalization and the tuning of the penalty parameters is done by k-fold cross validation.

One option is to penalize the VAR coefficients by hierarchical group LASSO regularization and the other option is the standard LASSO also known as L1 regularization. For hierarchical group LASSO the user must set \texttt{penalty=“HLag”} and for standard LASSO penalty=“LASSO”. In the \texttt{psychNET} function, \texttt{penalty} argument corresponds to the \texttt{VARpen} and \texttt{VARXpen} arguments of the functions \texttt{sparseVAR} and \texttt{sparseVARX} respectively, while \texttt{lag} is associated with the parameter \texttt{p} of these two functions. Typically, the function internally calculates a grid for the regularization parameter corresponding to sparse penalty. The user can provide her/his own grid of regularization parameters with the argument \texttt{lambda1}. The latter acts like the arguments \texttt{VAR1seq} and \texttt{VARX1Phiseq} of the original functions \texttt{sparseVAR} and \texttt{sparseVARX} respectively. Other arguments of these functions can be passed via the ... structure of the \texttt{psychNET} function. If you want the function to estimate the lag of the process simultaneously you must set \texttt{lag=NULL}. For details on the original functions and additional parameters that can be used you can look at \texttt{?bigtime::sparseVAR} and \texttt{?bigtime::sparseVARX}.

**Sparse VAR model with simultaneous covariance estimation (GVAR)**

A sparse VAR with simultaneous covariance estimation (also known as graphical VAR) is fitted by setting \texttt{model=“GVAR”}. This model is available with the R package \texttt{graphicalVAR} in the function \texttt{graphicalVAR}. The model parameters are estimated by optimizing a penalized maximum likelihood. The only penalization option when \texttt{model=“GVAR”} is LASSO, which means that \texttt{penalty} argument must be equal to ”LASSO”. The tuning of the penalty parameters is done by the extended Bayesian information criterion (EBIC) by setting \texttt{criterion=“EBIC”}. Model selection via standard BIC is possible by using an additional argument \texttt{gamma=0} in the \texttt{psychNET} function. This model uses two distinct penalties, one for the autoregressive parameters and one for the covariance parameters. Typically, the function calculates its own grid of penalty parameters for the regularization, however, the
user can provide her/his own grid by using the parameters $\lambda_1$ (for covariance penalization) and $\lambda_2$ (for autoregressive penalization) respectively in the function `psychNET`. Other arguments of the original `graphicalVAR` function can be passed via the ... structure of the `psychNET` function.

**!!WARNING!!** Do not use the ... to provide the following arguments of the `graphicalVAR` function: `vars`, `scale`, `idvar`, `beepvar`, `dayvar`, `centerWithin`, `deleteMissings` since they are already specified internally. If you want to use `idvar`, `beepvar`, `dayvar` arguments of the original function `graphicalVAR`, these variables must be provided as columns in the data object explicitly named as "ID", "BEEP", and "DAY" respectively. For `scale` and `centerWithin` arguments you can use the argument `transform` of the `psychNET` function. For details on the original function and additional parameters that can be used you can look at `?graphicalVAR::graphicalVAR`.

**Sparse VAR model for mixed type of time series (SMVAR)**

A sparse VAR with simultaneous covariance estimation (also known as graphical VAR) is fitted by setting `model="SMVAR"`. This model is available with the R package `mgm` in the function `mvar`. The model parameters are estimated by optimizing a penalized least squares function per equation. The only penalization option when `model="SMVAR"` is elasticnet, which means that `penalty` argument must be equal to "ENET". The tuning of the penalty parameters is done by the extended Bayesian information criterion (EBIC) by setting `criterion="EBIC"` or k-fold cross validation by setting `criterion="CV"`. Typically, the function internally calculates a grid for the regularization parameter. The user can provide her/his own grid of regularization parameters with the argument `lambda1`. The latter acts analogous to the argument `lambdaSeq` of the original `mvar` function. Model selection via standard BIC is possible by using an additional argument `gamma=0` in the `psychNET` function. Other arguments of the original `mvar` function can be passed via the ... structure of the `psychNET` function.

**!!WARNING 1!!** When `model="SMVAR"` the data must be given in a "data.frame" format with the following properties:

1. Gaussian variables: must be of class "numeric"
2. Poisson variables: must be of class "integer"
3. Categorical variables: must be of class "factor"
4. Ordinal variables: must be of class "ordered factor" (SMVAR for ordinal type of variables to be expected in a following version of the package `psychNET`).

**!!WARNING 2!!** Do not use the ... to provide the following arguments of the `mvar` function: `type`, `level`, `scale`, `beepvar`, `dayvar` since they are already specified internally. If you want to use `beepvar` and `dayvar` arguments of the original function `mvar`, these variables must be provided as columns in the data object explicitly named as "BEEP", and "DAY" respectively. For `scale` you can use the argument `transform` of the `psychNET` function. For details on the original function and additional parameters that can be used you can look at `?mgm::mvar`.

**Sparse VEC model (SVECM)**

A sparse VEC (vector error correction) model is fitted with the `psychNET` function by setting `model="SVECM"`. This model is implemented in the function `fitVECM` from the R package `sparsevar` and the unknown model parameters are estimated via penalized multivariate least squares. Three different types of penalization are available that can be passed to the function through the `penalty` argument. If you set `penalty="ENET"` an elasticnet penalty is applied to the parameters with other option being "SCAD" for SCAD type of penalization and "MCP" for MC+ penalty. The
only option available for tuning the penalty parameter is k-fold cross validation. The parameter lag of the psychNET function corresponds to the parameter p of the fitVECM function, the parameter penalty is used in the same way as in the fitVECM function while criterion substitutes the argument method of the fitVAR function. Additional arguments can be passed to the fitVAR function by using the ... structure of the psychNET function. For details on the original function and additional parameters that can be used you can look at ?sparsevar::fitVECM. The argument logScale of the orignal function is set to FALSE, but you can use the argument transform of the psychNET function instead.

Sparse VARMA model with hierarchical lag structures (SVARHLMA)

A sparse VARMA (vector autoregressive moving average) model that offers the possibility of simultaneous lag estimation is fitted by setting model="SVARHLMA". This model is available with the R package bigtime in the function sparseVARMA. The model parameters are estimated by penalized least squares optimized by a proximal gradient algorithm. The model offers two types of penalization and the tuning of the penalty parameters is done by k-fold cross validation. One option is to penalize the VAR coefficients by hierarchical group LASSO regularization and the other option is the standard LASSO. For hierarchical group LASSO the user must set penalty="HLag" and for standard LASSO penalty="LASSO". In the psychNET function, the penalty argument corresponds to the VARpen argument of the function sparseVARMA, while lag is associated with the parameter p of this function. Typically, the function internally calculates a grid for the regularization parameter corresponding to sparse penalty. The user can provide her/his own grid of regularization parameters with the argument lambda1. The latter acts like the arguments VARlseq of the original function sparseVARMA. Other arguments of this function can be passed via the ... structure of the psychNET function. If you want the function to estimate the lag of the process simultaneously you must set lag=NULL. For details on the original function and additional parameters that can be used you can look at ?bigtime::sparseVARMA.

Dynamic factor model (DFM)

A DFM is fitted by setting model="DFM" in the psychNET function. This model is available with the R package dynfactoR (available at github) in the function dfm. The model parameters are estimated by an EM algorithm. The argument nFact of the psychNET function is used to specify the number of static factors and it is analogous to the argument r of the original dfm function. The argument lag of the psychNET function is used to specify the lag order of the factor process analogously to the argument p of the dfm function. The DFM that we implement here is restricted to have an identity system state covariance matrix and zeros at the upper diagonal elements of the factor loading matrix for identifiability purposes. The user of the psychNET package can specify her/his own threshold for algorithm convergence by using an additional argument threshold.

Multi-level VAR model for group level dynamics (MLVAR)

An MLVAR can be fitted by setting model="MLVAR". This model is available with the R package mlVAR in the function mlVAR.

!!WARNING!! Do not use the ... to provide the following arguments of the mlVAR function: vars, scale, idvar, beepvar, dayvar, estimator, and scaleWithin since they are already specified internally. If you want to use idvar, beepvar, dayvar arguments of the original function mlVAR, these variables must be provided as columns in the data object explicitly named as "ID", "BEEP", and "DAY" respectively. For the scaleWithin argument you can use the argument transform of the psychNET function. For details on the original function and additional parameters that can be used you can look at ?mlVAR::mlVAR. The only estimation possible is "lmer".

Sparse VAR model with simultaneous covariance estimation for group level dynamics (GGVAR)
A sparse VAR with simultaneous covariance estimation for multiple individuals (also known as graphical VAR) is fitted by setting `model="GGVAR"`. This model is available with the R package `SparseTSCGM` in the function `sparse.tscgm`. The model parameters are estimated by optimizing a penalized maximum likelihood. Penalization options when `model="GGVAR"` is LASSO and SCAD, which means that penalty argument must be equal to "LASSO" for LASSO penalization and equal to "SCAD" for SCAD penalization. The tuning of the penalty parameters is done by AIC, BIC, EBIC, GIC (generalized information criterion), and MBIC (modified Bayesian information criterion) by using the criterion argument which is the same as the optimality argument in the `sparse.tscgm` function. This model uses two distinct penalties, one for the autoregressive parameters and one for the covariance parameters. Typically, the function calculates its own grid of penalty parameters for the regularization, however, the user can provide her/his own grid by using the parameters `lambda1` (for covariance penalization) and `lambda2` (for autoregressive penalization) respectively in the function `psychNET`. Other arguments of the original `graphicalVAR` function can be passed via the `...` structure of the `psychNET` function. Be aware that only VAR models with up to 2 lags are possible.

**Additional details** The `psychNET` function will estimate (based on the lag of the process) one or more temporal conditional independence graphs unless the `model` equals to "DFM". For `model="DFM"` and lag=1 the function will estimate the equivalent VAR(1), whereas for lag greater than one, the temporal network of the factor interactions will be estimated. Contemporaneous conditional independence graphs are available only when the `model` argument equals to: "GVAR", "GGVAR", "MLVAR", or "DFM" with one lag.

**Value**

The function `psychNET` returns a list object of class `pnt`.

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**References**


Examples

## load the psychNET library
library(psychNET)

## load the Canada dataset from the 'vars' package
data("Canada", package = "vars")
Canada_data_frame <- data.frame(Canada)

## fit a VAR model
VAR_model <- psychNET(Canada_data_frame, model = "VAR", lag = 1, type = "const")
# print the result
VAR_model
# summarize the resulting network
summary(VAR_model)
# summarize the VAR model using the original summary method
vars:::summary.varest(VAR_model$fit)
# plot the VAR model results using the original plot method
vars:::plot.varest(VAR_model$fit)
# plot the resulting network
plot(VAR_model)

## fit a sparse VAR model
sparse_VAR_model <- psychNET(Canada_data_frame, model = "SVAR", lag = 1)
# print the result
sparse_VAR_model
# summarize the resulting network
summary(sparse_VAR_model)
# plot the resulting network
plot(sparse_VAR_model)

## fit a sparse VAR model as the one in the 'bigtime' package
sparse_lassVAR_model <- psychNET(Canada_data_frame, model = "SVARHL", penalty = "LASSO", lag = 1, VARgran=c(500,1000))
# print the result
sparse_lassVAR_model
# summarize the resulting network
summary(sparse_lassVAR_model)
# plot the resulting network
plot(sparse_lassVAR_model)

## Load the psychNET package
library(psychNET)
## load the 'vars' package
library(vars)

## Load the Canada dataset from the vars package
data(Canada)

## check the structure of the data
str(Canada)

## The data is in time series format. It needs to be transformed into
## a matrix, data.frame or longitudinal object for the psychNET package
Canada_data_frame <- data.frame(Canada)

## fitting a VAR using the vars package
varmod <- vars::VAR(Canada, p = 2, type = "none")

## fitting the same VAR using the psychNET package
psychvar <- psychNET(Canada_data_frame, model = "VAR", lag = 2, type = "none")

## Check if the results are the same
all.equal(Acoef(varmod), psychvar$results$A, check.attributes = FALSE)

################################################################################
####### Fit A DYNAMIC FACTOR TO THE CANADA DATA FROM THE 'vars' PACKAGE ########
################################################################################

## install and load the 'devtools' package and the
## by using install.packages("devtools") and then
## library(devtools)
## install the 'dynfactoR' package available on github
## by using devtools::install_github("rbagd/dynfactoR")
## library(dynfactoR)

## Load the Canada dataset from the vars package
data(Canada, package = "vars")

## check the structure of the data
str(Canada)

## The data is in time series format. It needs to be transformed into
## a matrix, data.frame or longitudinal object for the psychNET package
Canada_data_frame <- data.frame(Canada)

## fitting a DFM using the dynfactoR package
dfmmod <- psychNET:::dfm(Canada_data_frame, r=2, p = 1,
                         rQ= "identity", rC= "upper",max_iter = 100000)

## fitting the same DFM using the psychNET package
psychdfm <- psychNET(Canada_data_frame, model = "DFM", nFact = 2, lag = 1)

## Check if the results are the same
all.equal(dfmmod$A, psychdfm$results$A_fact[[1]], check.attributes = FALSE)
all.equal(dfmod$C, psychdfm$results$B_fac_symptoms, check.attributes = FALSE)
all.equal(dfmod$Q, psychdfm$results$System_Covariance, check.attributes = FALSE)
all.equal(dfmod$R, psychdfm$results$Obs_Covariance, check.attributes = FALSE)

####################################################
### FIT A SPARSE VAR TO THE CANADA DATA FROM THE 'vars' PACKAGE ############
####################################################

## Load the Canada dataset from the vars package
data(Canada, package = "vars")

## The data is in time series format. It needs to be transformed into
## a matrix, data.frame or longitudinal object for the psychNET package
Canada_data_frame <- data.frame(Canada)

## fitting a SVAR using the sparsevar package
set.seed(1)
svarmod <- psychNET:::fitVAR(Canada, p = 1, penalty="SCAD", method="cv", logScale=FALSE)

## fitting the same SVAR using the psychNET package
set.seed(1)
psychsvar <- psychNET(Canada_data_frame, model = "SVAR", penalty = "SCAD", lag = 1, criterion="CV")

## Check if the results are the same
all.equal(svarmod$A, psychsvar$results$A, check.attributes = FALSE)

####################################################
#### EXAMPLE OF A SPARSE VAR WITH HIERARCHICAL LAGS FROM THE 'bigtime' PACKAGE ######
####################################################

## load the 'bigtime' package
library(bigtime)

## Load the Y dataset from the bigtime package
data(Y, package = "bigtime")

## fitting a SVAR with hierarchical lags
## using the bigtime package
svarhlmod <- sparseVAR(Y, VARpen ="HLag")

## fitting the same model using the psychNET package
psychsvarhl <- psychNET(Y, model = "SVARHL", penalty = "HLag", criterion="CV")

## Check if the results are the same
all.equal(svarhlmod$Phihat, psychsvarhl$fit$Phihat, check.attributes = FALSE)

####################################################
#### REPRODUCE EXAMPLE OF A SPARSE MIXED VAR FROM THE 'mgm' PACKAGE #######
####################################################

## load the 'mgm' package
library(mgm)

# 1) Define mVAR model as in the mgm manual
p <- 6 # Six variables
type <- c("c", "c", "c", "c", "g", "g") # 4 categorical, 2 gaussians
level <- c(2, 2, 4, 4, 1, 1) # 2 categorical with m=2, 2 categorical with m=4, two continuous
max_level <- max(level)
lags <- 1:3 # include lagged effects of order 1-3
n_lags <- length(lags)

# Specify thresholds
thresholds <- list()
thresholds[[1]] <- rep(0, level[1])
thresholds[[2]] <- rep(0, level[2])
thresholds[[3]] <- rep(0, level[3])
thresholds[[4]] <- rep(0, level[4])
thresholds[[5]] <- rep(0, level[5])
thresholds[[6]] <- rep(0, level[6])

# Specify standard deviations for the Gaussians
sds <- rep(NULL, p)
sds[5:6] <- 1

# Create coefficient array
coearray <- array(0, dim=c(p, p, max_level, max_level, n_lags))

# a.1) interaction between continuous 5<6, lag=3
coearray[5, 6, 1, 1, 2] <- .4
# a.2) interaction between 1<3, lag=1
m1 <- matrix(0, nrow=level[2], ncol=level[4])
m1[1, 1:2] <- 1
m1[2, 3:4] <- 1
coearray[1, 3, 1:level[2], 1:level[4], 1] <- m1
# a.3) interaction between 1<5, lag=9
coearray[1, 5, 1:level[1], 1:level[5], 3] <- c(0, 1)

# 2) Sample
set.seed(1)
dlist <- mvarsampler(coefarray = coearray,
                      lags = lags,
                      thresholds = thresholds,
                      sds = sds,
                      type = type,
                      level = level,
                      N = 200,
                      pbar = TRUE)

# 3) Transform data into a data.frame for psychoNET suitability
# each categorical variable is coded as factor, each poisson as integer, gaussian as numeric
d1 <- as.data.frame(dlist$data)
d1$V1 <- as.factor(d1$V1)
d1$V2 <- as.factor(d1$V2)
d1$V3 <- as.factor(d1$V3)
d1$V4 <- as.factor(d1$V4)
dat <- d1

## fitting the SMVAR model using the mgm package
smvarmod <- mvar(data = dlist$data,
                 type = type,
                 level = level,
                 lambdaSel = "EBIC",
                 lags = 1:3,
                 scale = FALSE,
                 signInfo = FALSE,
                 overparameterize = FALSE)

## fitting the same model using the psychNET package
psychsmvar <- psychNET(dat, model = "SMVAR",
                        lag = 3,
                        criterion = "EBIC",
                        signInfo = FALSE,
                        overparameterize = FALSE)

all.equal(smvarmod$wadj,psychsmvar$fit$wadj)

# load the 'mlVAR' package
library(mlVAR)

## Simulate data:
Model <- mlVARsim(nPerson = 50, nNode = 3, nTime = 50, lag=1)

# Estimate an MLVAR with correlated random effects using the mlVAR package
mlvarmod <- mlVAR(Model$Data, vars = Model$vars,
                  idvar = Model$idvar, lags = 1, temporal = "correlated")

# Estimate the same MLVAR using the psychNET package
psychmlvar <- psychNET(Model$Data, model="MLVAR", lag = 1, temporal = "correlated")

# Check if the results are equal
all.equal(mlvarmod$results, psychmlvar$fit$results)
### load the 'SparseTSCGM' package

```r
library(SparseTSCGM)
```

### Simulate data:

```r
seed = 321
datas <- sim.data(model="ar1", time=10, n.obs=10, n.var=5, seed=seed, prob0=0.35, network="random")
data.fit <- datas$data1
```

# Estimate a group graphical VAR (also known as time series chain graphical model) # using the SparseTSCGM package

```r
ggvarmod <- sparse.tscgm(data=data.fit,
                          lam1=NULL, lam2=NULL, nlambda=NULL,
                          model="ar1", penalty="scad", optimality="bic",
                          control=list(maxit.out = 10, maxit.in = 100))
```

# Estimate the same model using the psychNET package

```r
psychggvar <- psychNET(data.fit, model="GGVAR", lag=1, penalty="SCAD", criterion="BIC",
                        control=list(maxit.out = 10, maxit.in = 100))
```

# Check if the results are equal

```r
all.equal(ggvarmod$theta, psychggvar$fit$theta, check.attributes = FALSE)
all.equal(ggvarmod$gamma, psychggvar$fit$gamma, check.attributes = FALSE)
```

---

**summary.pnt**

*Summary method for S3 class "pnt" objects.*

**Description**

Generic function that is used in order to summarize information from "pnt" class objects.

**Usage**

```r
## S3 method for class 'pnt'
summary(object, ...)
```

**Arguments**

- **object**: An object obtained by the psychNET function.
- **...**: Not used in this version of the package.

**Details**

This a generic function that summarize the information of the networks obtained after a time series model has been fitted to data. Since the main function psychNET is a wrapper of several models the summary methods of each method can also be used (if available) by typing `summary(object$fit)` where object is an object obtained by the psychNET function.
Value

The function `summary.pnt` returns a list with the following components:

- **contemporaneous**: When estimates of the covariance matrix (contemporaneous network) are available then contemporaneous is a list with two components named local and global that describe the contemporaneous network locally and globally. For global description of the network, transitivity, reciprocity, distance, density, and diameter are returned in a one column matrix. At the local (nodes) level the function calculates node transitivity, the degree centrality, step-1 and -2 node expected influence, betweenness centrality and closeness centrality.

- **temporal**: A list with two components named local and global that describe the temporal network locally and globally. At the global graph level the same descriptives as in the contemporaneous network are returned for each lag of the VAR model. At the local level, node transitivity, in and out degree centrality, step -1 and -2 expected influence centralities, betweenness, out and in closeness centralities are returned to the user.

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References


Index

*Topic datasets
  MIR, 4
  MOOVD, 6
*Topic package
  psychNET-package, 2

MIR, 4
MOOVD, 6

plot.pnt, 7
print.pnt, 9
psychNET, 9, 10
psychNET-package, 2

summary.pnt, 21