

Package ‘matrixpls’

April 28, 2021

Encoding UTF-8

Type Package

Title Matrix-Based Partial Least Squares Estimation

Version 1.0.13

Date 2021-04-28

Maintainer Mikko Rönkkö <mikko.ronkko@jyu.fi>

Description Partial Least Squares Path Modeling algorithm and related algorithms. The algorithm implementations aim for computational efficiency using matrix algebra and covariance data. The package is designed toward Monte Carlo simulations and includes functions to perform simple Monte Carlo simulations.

URL <https://github.com/mronkko/matrixpls>

BugReports <https://github.com/mronkko/matrixpls/issues>

ByteCompile TRUE

Imports assertive, matrixcalc, lavaan, MASS, methods, psych

Suggests simsem, RUnit, parallel, semPLS, boot, Matrix, ASGSCA, knitr, R.rsp

License GPL-3

LazyLoad yes

LazyData true

RoxygenNote 7.1.1

Collate 'convCheck.R' 'estimator.R' 'innerEstim.R' 'matrixpls.R'
'matrixpls.boot.R' 'matrixpls.crossvalidate.R'
'matrixpls.optim.R' 'matrixpls.plspm.R'
'matrixpls.postestimation.R' 'matrixpls.predict.R'
'matrixpls.sempls.R' 'matrixpls.sim.R' 'matrixpls.util.R'
'outerEstim.R' 'paramEstimator.R' 'reliabilityEstim.R'
'signChange.R' 'weightFun.R' 'weightSign.R'

VignetteBuilder R.rsp

Depends R (>= 2.10)

NeedsCompilation no

Author Mikko Rönkkö [aut, cre]

Repository CRAN

Date/Publication 2021-04-28 14:10:05 UTC

R topics documented:

matrixpls-package	3
ave	5
cei	6
convCheck	7
cr	8
effects.matrixpls	9
estimator	9
fitSummary	13
fitted.matrixpls	14
gof	14
GSCA	15
htmt	17
innerEstim	18
loadings	19
matrixpls	20
matrixpls-common	22
matrixpls-functions	23
matrixpls.crossvalidate	24
matrixpls.plspm	25
matrixpls.sempls	28
matrixpls.sim	30
matrixplsboot	33
optimCrit	36
outerEstim	37
parameterEstim	38
predict.matrixpls	40
q2	42
r2	43
reliabilityEstim	44
residuals.matrixpls	45
satisfaction	46
signChange	47
weightFun	48
weightSign	53

Index

55

Description

matrixpls calculates composite variable models using partial least squares (PLS) algorithm and related methods. In contrast to most other PLS software which implement the raw data version of the algorithm, **matrixpls** works with data covariance matrices. The algorithms are designed to be computationally efficient, modular in programming, and well documented. **matrixpls** integrates with **simsem** to enable Monte Carlo simulations with as little custom programming as possible.

Details

matrixpls calculates models where sets of indicator variables are combined as weighted composites. These composites are then used to estimate a statistical model describing the relationships between the composites and composites and indicators. While a number of such methods exists, the partial least squares (PLS) technique is perhaps the most widely used.

The **matrixpls** package implements a collection of PLS techniques as well as the more recent GSCA and PLSc techniques and older methods based on analysis with composite variables, such as regression with unit weighted composites or factor scores. The package provides a unified framework that enables the comparison and analysis of these algorithms. In contrast to previous R packages for PLS, such as **plspm** and **semPLS** and all currently available commercial PLS software, which work with raw data, **matrixpls** calculates the indicator weights and model estimates from data covariance matrices. Working with covariance data allows for reanalyzing covariance matrices that are sometimes published as appendices of articles, is computationally more efficient, and lends itself more easily for formal analysis than implementations based on raw data.

matrixpls has modular design that is easily expanded and contains more calculation options than the two other PLS packages for R. To allow validation of the algorithms by end users and to help porting existing analysis files from the two other R packages to **matrixpls**, the package contains compatibility functions for both **plspm** and **semPLS**.

The design principles and functionality of the package is best explained by first explaining the main function `matrixpls`. The function performs two tasks. It first calculates a set of indicator weights to form composites based on data covariance matrix and then estimates a statistical model with the indicators and composites using the weights. The main function takes the following arguments:

```
matrixpls(S, model, W.model = NULL,
          weightFun = weightFun.pls,
          parameterEstim = parameterEstim.separate,
          weightSign = NULL, ...,
          validateInput = TRUE, standardize = TRUE)
```

The first five arguments of `matrixpls` are most relevant for understanding how the package works. `S`, is the data covariance or correlation matrix. `model` defines the model which is estimated in the second stage and `W.model` defines how the indicators are to be aggregated as composites. If `W.model` is left undefined, it will be constructed based on `model` following rules that are explained elsewhere in the documentation. `weightFun` and `parameterEstim` are functions that implement the

first and second task of the function respectively. All other arguments are passed down to these two functions, which in turn can pass arguments to other functions that they call.

Many of the commonly used arguments of `matrixpls` function are functions themselves. For example, executing a PLS analysis with Mode B outer estimation for all indicator blocks and centroid inner estimation could be specified as follows:

```
matrixpls(S, model,
          outerEstim = outerEstim.modeB,
          innerEstim = innerEstim.centroid)
```

The arguments `outerEstim` and `innerEstim` are not defined by the `matrixpls` function, but are passed down to `weightFun.pls` which is used as the default `weightFun`. `outerEstim.modeB` and `innerEstim.centroid` are themselves functions provided by the **matrixpls** package, which perform the actual inner and outer estimation stages of the PLS algorithm. Essentially, all parts of the estimation algorithm can be provided as arguments for the main function. This allows for adjusting the inner workings of the algorithm in a way that is currently not possible with any other PLS software.

It is also possible to define custom functions. For example, we could define a new Mode B outer estimator that only produces positive weights by creating a custom function:

```
myModeB <- function(...){
  abs(outerEstim.ModeB(...))
}

matrixpls(S, model,
          outerEstim = myModeB,
          innerEstim = innerEstim.centroid)
```

Model can be specified in the lavaan format or the native `matrixpls` format. The native model format is a list of three binary matrices, `inner`, `reflective`, and `formative` specifying the free parameters of a model: `inner` (1×1) specifies the regressions between composites, `reflective` ($k \times 1$) specifies the regressions of observed data on composites, and `formative` ($1 \times k$) specifies the regressions of composites on the observed data. Here k is the number of observed variables and 1 is the number of composites.

If the model is specified in lavaan format, the native format model is derived from this model by assigning all regressions between latent variables to `inner`, all factor loadings to `reflective`, and all regressions of latent variables on observed variables to `formative`. Regressions between observed variables and all free covariances are ignored. All parameters that are specified in the model will be treated as free parameters.

The original papers about Partial Least Squares, as well as many of the current PLS implementations, impose restrictions on the matrices `inner`, `reflective`, and `formative`: `inner` must be a lower triangular matrix, `reflective` must have exactly one non-zero value on each row and must have at least one non-zero value on each column, and `formative` must only contain zeros. Some PLS implementations allow `formative` to contain non-zero values, but impose a restriction that the sum of `reflective` and `t(formative)` must satisfy the original restrictions of `reflective`. The only restrictions that `matrixpls` imposes on `inner`, `reflective`, and `formative` is that these must be binary matrices and that the diagonal of `inner` must be zeros.

Author(s)

Maintainer: Mikko Rönkkö <mikko.ronkko@jyu.fi>

References

Rosseel, Y. (2012). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software*, 48(2), 1–36. Retrieved from <http://www.jstatsoft.org/v48/i02>

Lohmöller J.-B. (1989) *Latent variable path modeling with partial least squares*. Heidelberg: Physica-Verlag.

Rönkkö, M., McIntosh, C. N., & Antonakis, J. (2015). On the adoption of partial least squares in psychological research: Caveat emptor. *Personality and Individual Differences*, (87), 76–84. doi: [10.1016/j.paid.2015.07.019](https://doi.org/10.1016/j.paid.2015.07.019) DOI:10.1016/j.paid.2015.07.019

Wold, H. (1982). Soft modeling - The Basic Design And Some Extensions. In K. G. Jöreskog & S. Wold (Eds.), *Systems under indirect observation: causality, structure, prediction* (pp. 1–54). Amsterdam: North-Holland.

See Also

Useful links:

- <https://github.com/mronkko/matrixpls>
- Report bugs at <https://github.com/mronkko/matrixpls/issues>

 ave

Average Variance Extracted indices for matrixpls results

Description

The `matrixpls` method for the generic function `ave` computes Average Variance Extracted indices for the model using the formula presented by Fornell and Larcker (1981).

Usage

```
ave(object, ...)
```

Arguments

`object` `matrixpls` estimation result object produced by the `matrixpls` function.
`...` All other arguments are ignored.

Value

A list containing the Average Variance Extracted indices in the first position and the differences between `aves` and largest squared correlations with other composites in the second position.

References

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 18(1), 39–50.

See Also

Other post-estimation functions: [cei\(\)](#), [cr\(\)](#), [effects.matrixpls\(\)](#), [fitSummary\(\)](#), [fitted.matrixpls\(\)](#), [gof\(\)](#), [htmt\(\)](#), [loadings\(\)](#), [predict.matrixpls\(\)](#), [r2\(\)](#), [residuals.matrixpls\(\)](#)

 cei

Composite Equivalence Indices

Description

The `matrixpls` method for the generic function `cei` computes composite equivalence indices (CEI) for the `matrixpls` object. By default, the composites are compared against unit-weighted composites.

Usage

```
cei(object, object2 = NULL, ...)
```

Arguments

<code>object</code>	matrixpls estimation result object produced by the matrixpls function.
<code>object2</code>	Another <code>matrixpls</code> object that <code>matrixpls</code> is compared against.
<code>...</code>	All other arguments are ignored.

Details

Composite equivalence indices quantify if two sets of composites calculated from the same data using different weight algorithms differ. Composites are matched by name and correlations for each pair are reported.

Value

Composite equivalence indices as a vector

See Also

Other post-estimation functions: [ave\(\)](#), [cr\(\)](#), [effects.matrixpls\(\)](#), [fitSummary\(\)](#), [fitted.matrixpls\(\)](#), [gof\(\)](#), [htmt\(\)](#), [loadings\(\)](#), [predict.matrixpls\(\)](#), [r2\(\)](#), [residuals.matrixpls\(\)](#)

Examples

```
# Load the Tenenhaus et al 2005 model and data from semPLS
library(semPLS)
data(ECSImobi)
data(mobi)

# Reflective and empty formative model
reflective<- ECSImobi$M
formative <- t(reflective)
formative[] <- 0

# Estimation using covariance matrix
model <- list(inner = t(ECSImobi$D),
              reflective = reflective,
              formative = formative)

S <- cor(mobi)

matrixpls.ModeA <- matrixpls(S, model, innerEstim = innerEstim.centroid)
matrixpls.Fixed <- matrixpls(S, model, weightFun = weightFun.fixed)

cei(matrixpls.ModeA)
cei(matrixpls.ModeA, matrixpls.Fixed)
```

convCheck

Convergence checks

Description

The convergence check functions compare two weight matrices and returns the value of the convergence criterion describing the difference between the two weight matrices.

Usage

```
convCheck.relative(Wnew, Wold)
```

```
convCheck.square(Wnew, Wold)
```

```
convCheck.absolute(Wnew, Wold)
```

Arguments

Wnew	Current weight matrix
Wold	Weight matrix from the previous iteration

Value

Scalar value of the convergence criterion

Functions

- `convCheck.relative`: maximum of relative differences between weights from two iterations
- `convCheck.square`: maximum of squared absolute differences between weights from two iterations.
- `convCheck.absolute`: maximum of absolute differences between weights from two iterations

 cr

Composite Reliability indices for matrixpls results

Description

The `matrixpls` method for the generic function `cr` computes Composite Reliability indices for the model using the formula presented by Fornell and Larcker (1981).

Usage

```
cr(object, ...)
```

Arguments

`object` `matrixpls` estimation result object produced by the `matrixpls` function.
`...` All other arguments are ignored.

Value

A named numeric vector containing the Composite Reliability indices.

References

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 18(1), 39–50.

Aguirre-Urreta, M. I., Marakas, G. M., & Ellis, M. E. (2013). Measurement of composite reliability in research using partial least squares: Some issues and an alternative approach. *The DATA BASE for Advances in Information Systems*, 44(4), 11–43. doi: [10.1145/2544415.2544417](https://doi.org/10.1145/2544415.2544417) DOI:10.1145/2544415.2544417

See Also

Other post-estimation functions: `ave()`, `cei()`, `effects.matrixpls()`, `fitSummary()`, `fitted.matrixpls()`, `gof()`, `hmtt()`, `loadings()`, `predict.matrixpls()`, `r2()`, `residuals.matrixpls()`

effects.matrixpls *Total, Direct, and Indirect Effects for matrixpls results*

Description

The `matrixpls` method for the standard generic function `effects` computes total, direct, and indirect effects for a `matrixpls` results according to the method described in Fox (1980).

Adapted from the `effects` function of the `sem` package

Usage

```
## S3 method for class 'matrixpls'
effects(object, ...)
```

Arguments

`object` `matrixpls` estimation result object produced by the `matrixpls` function.
`...` All other arguments are ignored.

Value

A list with Total, Direct, and Indirect elements.

References

Fox, J. (1980) Effect analysis in structural equation models: Extensions and simplified methods of computation. *Sociological Methods and Research* 9, 3–28.

See Also

Other post-estimation functions: `ave()`, `cei()`, `cr()`, `fitSummary()`, `fitted.matrixpls()`, `gof()`, `htmt()`, `loadings()`, `predict.matrixpls()`, `r2()`, `residuals.matrixpls()`

estimator *Parameter estimation of a model matrix*

Description

Estimates the parameters of a model matrix (inner, reflective, or formative).

Usage

```
estimator.ols(S, modelMatrix, W, ..., C = NULL, IC = NULL, n = NULL)
```

```
estimator.tsls(S, modelMatrix, W, ..., C)
```

```
estimator.plscLoadings(S, modelMatrix, W, ...)
```

```
estimator.efaLoadings(S, modelMatrix, W, ..., fm = "minres")
```

```
estimator.cfaLoadings(S, modelMatrix, W, ...)
```

```
estimator.plsreg(S, modelMatrix, W, ..., C)
```

Arguments

S	Covariance matrix of the data.
modelMatrix	A model matrix with dependent variables on rows, independent variables on columns, and non-zero elements indicating relationships. Can be either inner, reflective, or formative matrix.
W	Weight matrix, where the indicators are on columns and composites are on the rows.
...	All other arguments are either ignored or passed through to third party estimation functions.
C	Correlation matrix of the composites.
IC	Correlation matrix of the composites and indicators.
n	sample size, used for calculating standard errors.
fm	factoring method for estimating the factor loadings. Passed through to fa .

Details

Parameter estimation functions estimate the parameters of a model matrix (inner, reflective, or formative). These functions can be used as `parametersInner`, `parametersReflective`, and `parametersFormative` arguments for [parameterEstim.separate](#).

When two-stage least squares regression is applied with `estimator.tsls`, all exogenous variables are used as instrumental variables. There is currently no check of whether the number of instrumental variables is sufficient for estimation.

`estimator.plscLoadings` estimates the loadings by scaling the weights `W` with the correction factor `c` presented by Dijkstra (2011). This produces a MINRES estimator, which constraints the loadings to be proportional to the weights. The PLSc code is loosely based on code contributed by Wenjing Huang and developed with the guidance by Theo Dijkstra.

`estimator.plscLoadings` estimates loadings with an unconstrained single factor model, which requires at least three indicators per block. The loadings of single indicator factors are estimated as 1 and two indicator factors as estimated by the square root of the indicator correlation.

Providing `C` or `IC` allows for using disattenuated or otherwise adjusted correlation matrices. If not provided, these matrices are calculated using `S` and `W`.

A part of the code for [estimator.plsreg](#) is adopted from the `plspm` package, licensed under GPL3.

Value

A matrix with estimated parameters or a list of two matrices containing estimates and standard errors.

Functions

- `estimator.ols`: parameter estimation with OLS regression. Can be applied to inner, reflective, or formative matrix.
- `estimator.tsls`: parameter estimation with two-stage least squares regression. For inner matrix only.
- `estimator.plscLoadings`: parameter estimation with Dijkstra's (2011) PLSc correction for loadings. For reflective matrix only.
- `estimator.efaLoadings`: parameter estimation with one indicator block at a time with exploratory factor analysis. Minres estimation is implemented natively and all other estimation techniques use the `fa` function from the `psych` package. For reflective matrix only.
- `estimator.cfaLoadings`: Estimates a maximum likelihood confirmatory factor analysis with `lavaan`. For reflective matrix only.
- `estimator.plsreg`: parameter estimation with PLS regression. For inner matrix only.

Author(s)

Mikko Rönkkö, Wenjing Huang, Theo Dijkstra

Mikko Rönkkö, Gaston Sanchez, Laura Trinchera, Giorgio Russolillo

References

Huang, W. (2013). *PLSe: Efficient Estimators and Tests for Partial Least Squares* (Doctoral dissertation). University of California, Los Angeles.

Dijkstra, T. K. (2011). Consistent Partial Least Squares estimators for linear and polynomial factor models. A report of a belated, serious and not even unsuccessful attempt. Comments are invited. Retrieved from <http://www.rug.nl/staff/t.k.dijkstra/consistent-pls-estimators.pdf>

Sanchez, G. (2013). *PLS Path Modeling with R*. Retrieved from <http://www.gastonsanchez.com/PLS Path Modeling with R.pdf>

Examples

```
# Run the education example from the book

# Sanchez, G. (2013) PLS Path Modeling with R
# Trowchez Editions. Berkeley, 2013.
# http://www.gastonsanchez.com/PLS Path Modeling with R.pdf

education <- read.csv("http://www.gastonsanchez.com/education.csv")

Support <- c(0, 0, 0, 0, 0, 0)
Advising <- c(0, 0, 0, 0, 0, 0)
Tutoring <- c(0, 0, 0, 0, 0, 0)
```

```

Value <- c(1, 1, 1, 0, 0, 0)
# Omit two paths (compared to the model in the book) to achieve
# identification of the 2SLS analysis
Satisfaction <- c(0, 0, 1, 1, 0, 0)
Loyalty <- c(0, 0, 0, 0, 1, 0)

inner <- rbind(Support, Advising, Tutoring, Value, Satisfaction, Loyalty)

reflective <- diag(6)[c(rep(1,4),
                      rep(2,4),
                      rep(3,4),
                      rep(4,4),
                      rep(5,3),
                      rep(6,4)),]
formative <- matrix(0, 6, 23)

colnames(inner) <- colnames(reflective) <- rownames(formative) <- rownames(inner)
rownames(reflective) <- colnames(formative) <- colnames(education)[2:24]

education.model <- list(inner = inner,
                       reflective = reflective,
                       formative = formative)

# Reverse code two variables
education[,c("sup.under", "loy.asha")] <- - education[,c("sup.under", "loy.asha")]

S <- cor(education[,2:24])

# PLSc with OLS regression

education.out <- matrixpls(S, education.model,
                          disattenuate = TRUE,
                          parametersReflective = estimator.plscLoadings)

# PLSc with 2SLS regression

education.out2 <- matrixpls(S, education.model,
                           disattenuate = TRUE,
                           parametersReflective = estimator.plscLoadings,
                           parametersInner = estimator.tsls)

# Disattenuated regression with unit-weighted scales and exploratory factor analysis
# reliability estimates (with unconstrained MINRES estimator)

education.out3 <- matrixpls(S, education.model,
                           disattenuate = TRUE,
                           weightFun = weightFun.fixed,
                           parametersReflective = estimator.efaLoadings)

# Disattenuated GSCA with 2SLS regression after disattenuated based on
# confirmatory factor analysis reliability estimates

```

```

education.out4 <- matrixpls(S,education.model,
                           disattenuate = TRUE,
                           innerEstim = innerEstim.gsca,
                           outerEstim = outerEstim.gsca,
                           parametersInner = estimator.tsls,
                           parametersReflective = estimator.cfaLoadings)

# Compare the results

cbind(PLSc = education.out, PLSc_2sls = education.out2,
      DR = education.out3, GSCAc = education.out4)

# Compare the reliability estimates

cbind(PLSc = attr(education.out,"Q"), PLSc_2sls = attr(education.out2,"Q"),
      DR = attr(education.out3,"Q"), GSCAc = attr(education.out4,"Q"))

```

fitSummary

Summary of model fit of PLS model

Description

fitSummary computes a list of statistics that are commonly used to access the overall fit of the PLS model.

Usage

```
fitSummary(object, ...)
```

Arguments

object	matrixpls estimation result object produced by the matrixpls function.
...	All other arguments are ignored.

Value

A list containing a selection of fit indices.

See Also

Other post-estimation functions: [ave\(\)](#), [cei\(\)](#), [cr\(\)](#), [effects.matrixpls\(\)](#), [fitted.matrixpls\(\)](#), [gof\(\)](#), [hmt\(\)](#), [loadings\(\)](#), [predict.matrixpls\(\)](#), [r2\(\)](#), [residuals.matrixpls\(\)](#)

fitted.matrixpls	<i>Model implied covariance matrix based on matrixpls results</i>
------------------	---

Description

The `matrixpls` method for generic function `fitted` computes the model implied covariance matrix by combining `inner`, `reflective`, and `formative` as a simultaneous equations system. The error terms are constrained to be uncorrelated and covariances between exogenous variables are fixed at their sample values. Defining a composite as dependent variable in both `inner` and `formative` creates an impossible model and results in an error.

Usage

```
## S3 method for class 'matrixpls'
fitted(object, ...)
```

Arguments

<code>object</code>	matrixpls estimation result object produced by the <code>matrixpls</code> function.
<code>...</code>	All other arguments are ignored.

Value

a matrix containing the model implied covariances.

See Also

Other post-estimation functions: `ave()`, `cei()`, `cr()`, `effects.matrixpls()`, `fitSummary()`, `gof()`, `hmt()`, `loadings()`, `predict.matrixpls()`, `r2()`, `residuals.matrixpls()`

gof	<i>Goodness of Fit indices for matrixpls results</i>
-----	--

Description

The `matrixpls` method for the generic function `gof` computes the Goodness of Fit index for `matrixpls` results.

Usage

```
gof(object, ...)
```

Arguments

<code>object</code>	matrixpls estimation result object produced by the <code>matrixpls</code> function.
<code>...</code>	All other arguments are ignored.

Value

The Goodness of Fit index.

References

Henseler, J., & Sarstedt, M. (2013). Goodness-of-fit indices for partial least squares path modeling. *Computational Statistics*, 28(2), 565–580. doi: [10.1007/s0018001203171](https://doi.org/10.1007/s0018001203171)

See Also

Other post-estimation functions: [ave\(\)](#), [cei\(\)](#), [cr\(\)](#), [effects.matrixpls\(\)](#), [fitSummary\(\)](#), [fitted.matrixpls\(\)](#), [htmt\(\)](#), [loadings\(\)](#), [predict.matrixpls\(\)](#), [r2\(\)](#), [residuals.matrixpls\(\)](#)

GSCA

Generalized structured component analysis (GSCA) weights

Description

When used with [weightFun.pls](#), [innerEstim.gsca](#) and [outerEstim.gsca](#) implement the generalized structured component analysis indicator weighting system. Using [weightFun.optim](#) with the [optimCrit.gsca](#) optimization criterion provides an alternative approach to calculate GSCA weights by direct numerical minimization of the GSCA criterion function.

Details

The two step GSCA weight algorithm is designed to minimize.

$$SS(ZV-ZWA)$$

The parameter matrix A contains all model parameters including inner, reflective inner, and formative. The weight matrices V and W, which can contain duplicate elements, contain the indicator weights.

The first step of GSCA estimation method is calculation of regressions coefficients A given weights W and V. The function [innerEstim.gsca](#) update the part of A corresponding to regressions between the composites, corresponding to E matrix in [matrixpls](#). The regressions between composites and indicators are estimated in [outerEstim.gsca](#).

This algorithm for estimating the relationships between the composites is therefore identical to the PLS path weighting scheme with the exception that correlations are not used for inverse relationships and there is no falling back to identity scheme for composites that are not connected to other composites The second step of GSCA is calculating a new set of weights conditional on the regression coefficients A to minimize the sum of error terms in the regressions. This step is implemented in [outerEstim.gsca](#) after updating the regressions between indicators and composites. The implementation of GSCA in [matrixpls](#) differs from the Hwang & Takane (2004) version in that during the first step, only regressions between composites are estimated. The regressions between composites and indicators are estimated by the second stage the indicators and composites. Since these covariances need to be calculated in the second step, it is more efficient to not calculate them during the first step.

A part of the code for [outerEstim.gsca](#) is adopted from the **ASGCA** package, licensed under GPL3.

Author(s)

Mikko Rönkkö, Hela Romdhani, Stepan Grinek, Heungsun Hwang, Aurelie Labbe.

References

Hwang, H., & Takane, Y. (2004). Generalized structured component analysis. *Psychometrika*, 69(1), 81–99. doi: [10.1007/BF02295841](https://doi.org/10.1007/BF02295841)

Hela Romdhani, Stepan Grinek, Heungsun Hwang and Aurelie Labbe. (2014). ASGSCA: Association Studies for multiple SNPs and multiple traits using Generalized Structured Equation Models. R package version 1.4.0.

Examples

```
if(!require(ASGSCA)){
  print("This example requires the ASGSCA package from Bioconductor")
} else{
  # Run the example from ASGSCA package using GSCA estimation

  data(GenPhen)
  W0 <- matrix(c(rep(1,2),rep(0,8),rep(1,2),rep(0,8),rep(1,3),rep(0,7),rep(1,2)),
              nrow=8,ncol=4)
  B0 <- matrix(c(rep(0,8),rep(1,2),rep(0,3),1,rep(0,2)),nrow=4,ncol=4)

  # Set seed because ASGSCA uses random numbers as starting values
  set.seed(1)

  GSCA.res <-GSCA(GenPhen,W0, B0,estim=TRUE,path.test=FALSE,
                 latent.names=c("Gene1", "Gene2",
                                "Clinical pathway 1",
                                "Clinical pathway 2"))

  # Setup matrixpls to estimate the same model. Note that ASGSCA places dependent
  # variables on columns but matrixpls uses rows for dependent variables

  inner <- t(B0)
  formative <- t(W0)
  reflective <- matrix(0,8,4)

  colnames(formative) <- rownames(reflective) <- names(GenPhen)

  colnames(inner) <- rownames(inner) <-
  rownames(formative) <- colnames(reflective) <-
  c("Gene1", "Gene2", "Clinical pathway 1", "Clinical pathway 2")

  model <- list(inner = inner,
               reflective = reflective,
               formative = formative)

  # Estimate using alternating least squares

  matrixpls.res1 <- matrixpls(cov(GenPhen), model,
```



```

        outerEstim = outerEstim.gsca,
        innerEstim = innerEstim.gsca)

# Estimate using direct minimization of the estimation criterion
# Set the convergence criterion to be slightly stricter than normally
# to get identical results

matrixpls.res2 <- matrixpls(cov(GenPhen), model,
                           weightFun = weightFun.optim,
                           optimCrit = optimCrit.gsca,
                           control = list(reltol = 1e-12))

# Compare the weights

do.call(cbind,lapply(list(ASGSCA =GSCA.res[["Weight"]],
                        matrixpls_als = t(attr(matrixpls.res1,"W")),
                        matrixpls_optim =t(attr(matrixpls.res2,"W"))),
                    function(W) W[W!=0]))

# Check the criterion function values

optimCrit.gsca(matrixpls.res1)
optimCrit.gsca(matrixpls.res2)

}

```

htmt

Heterotrait-monotrait ratio

Description

The `matrixpls` method for the generic function `htmt` computes Heterotrait-monotrait ratio for the model using the formula presented by Henseler et al (2014).

Usage

```
htmt(object, ...)
```

Arguments

`object` `matrixpls` estimation result object produced by the `matrixpls` function.
`...` All other arguments are ignored.

Value

Heterotrait-monotrait ratio as a scalar

References

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.

See Also

Other post-estimation functions: `ave()`, `cei()`, `cr()`, `effects.matrixpls()`, `fitSummary()`, `fitted.matrixpls()`, `gof()`, `loadings()`, `predict.matrixpls()`, `r2()`, `residuals.matrixpls()`

innerEstim	<i>PLS inner estimation</i>
------------	-----------------------------

Description

Calculates a set of inner weights.

Usage

```
innerEstim.centroid(S, W, inner.mod, ignoreInnerModel = FALSE, ...)
```

```
innerEstim.path(S, W, inner.mod, ...)
```

```
innerEstim.factor(S, W, inner.mod, ignoreInnerModel = FALSE, ...)
```

```
innerEstim.identity(S, W, inner.mod, ...)
```

```
innerEstim.gsca(S, W, inner.mod, ...)
```

Arguments

S	Covariance matrix of the data.
W	Weight matrix, where the indicators are on columns and composites are on the rows.
inner.mod	A square matrix specifying the relationships of the composites in the model.
ignoreInnerModel	Should the inner model be ignored and all correlations be used.
...	Other arguments are ignored.

Details

In the centroid scheme, inner weights are set to the signs (1 or -1) of correlations between composites that are connected in the model specified in `inner.mod` and zero otherwise.

In the path scheme, inner weights are based on regression estimates of the relationships between composites that are connected in the model specified in `inner.mod`, and correlations for the inverse relationships. If a relationship is reciprocal, regression is used for both directions.

In the factor scheme, inner weights are set to the correlations between composites that are connected in the model specified in `inner.mod` and zero otherwise.

In the identity scheme identity matrix is used as the inner weight matrix E.

Centroid, inner, and path schemes fall back to to identity scheme for composites that are not connected to any other composites.

For information about GSCA weights, see [GSCA](#).

Value

A matrix of unscaled inner weights E with the same dimensions as `inner.mod`.

Functions

- `innerEstim.centroid`: inner estimation with centroid scheme.
- `innerEstim.path`: inner estimation with path scheme.
- `innerEstim.factor`: inner estimation with factor scheme.
- `innerEstim.identity`: inner estimation with identity scheme.
- `innerEstim.gsc`: inner estimation with generalized structured component analysis.

References

Lohmöller J.-B. (1989) *Latent variable path modeling with partial least squares*. Heidelberg: Physica-Verlag.

loadings

Factor loadings matrix from matrixpls results

Description

The `matrixpls` method for the generic function `loadings` computes standardized factor loading matrix from the model results.

Usage

```
loadings(object, ...)
```

Arguments

`object` matrixpls estimation result object produced by the `matrixpls` function.
`...` All other arguments are ignored.

Value

A matrix of estimated factor loadings.

See Also

Other post-estimation functions: [ave\(\)](#), [cei\(\)](#), [cr\(\)](#), [effects.matrixpls\(\)](#), [fitSummary\(\)](#), [fitted.matrixpls\(\)](#), [gof\(\)](#), [htmt\(\)](#), [predict.matrixpls\(\)](#), [r2\(\)](#), [residuals.matrixpls\(\)](#)

matrixpls

Partial Least Squares and other composite variable models.

Description

Estimates a weight matrix using Partial Least Squares or a related algorithm and then uses the weights to estimate the parameters of a statistical model.

Usage

```
matrixpls(
  S,
  model,
  W.model = NULL,
  weightFun = weightFun.pls,
  parameterEstim = parameterEstim.separate,
  weightSign = NULL,
  ...,
  validateInput = TRUE,
  standardize = TRUE
)
```

Arguments

S	Covariance matrix of the data.
model	There are two options for this argument: 1. lavaan script or lavaan parameter table, or 2. a list containing three matrices inner, reflective, and formative defining the free regression paths in the model.
W.model	An optional numeric matrix representing the weight pattern and starting weights (i.e. the how the indicators are combined to form the composite variables). If this argument is not specified, the weight patten is defined based on the relationships in the reflective and formative elements of model.
weightFun	A function for calculating indicator weights using the data covariance matrix S, a model specification model, and a weight pattern W.model. Returns a weight matrix W. The default is weightFun.pls
parameterEstim	A function for estimating the model parameters using the data covariance matrix S, model specification model, and weight matrix W. Returns a named vector of parameter estimates. The default is parameterEstim.separate
weightSign	A function for resolving weight sign ambiguity based on the data covariance matrix S and a weight matrix W. Returns a weight matrix W. See weightSign for details.

... All other arguments are passed through to `weightFun` and `parameterEstim`.
`validateInput` If TRUE, the arguments are validated.
`standardize` If TRUE, `S` is converted to a correlation matrix before analysis.

Details

`matrixpls` is the main function of the `matrixpls` package. This function parses a model object and then uses the results to call `weightFun` to calculate indicator weight. After this the `parameterEstim` function is applied to the indicator weights, the data covariance matrix, and the model object and the resulting parameter estimates are returned.

Model can be specified in the lavaan format or the native `matrixpls` format. The native model format is a list of three binary matrices, `inner`, `reflective`, and `formative` specifying the free parameters of a model: `inner` (1×1) specifies the regressions between composites, `reflective` ($k \times 1$) specifies the regressions of observed data on composites, and `formative` ($1 \times k$) specifies the regressions of composites on the observed data. Here k is the number of observed variables and 1 is the number of composites.

If the model is specified in lavaan format, the native format model is derived from this model by assigning all regressions between latent variables to `inner`, all factor loadings to `reflective`, and all regressions of latent variables on observed variables to `formative`. Regressions between observed variables and all free covariances are ignored. All parameters that are specified in the model will be treated as free parameters.

The original papers about Partial Least Squares, as well as many of the current PLS implementations, impose restrictions on the matrices `inner`, `reflective`, and `formative`: `inner` must be a lower triangular matrix, `reflective` must have exactly one non-zero value on each row and must have at least one non-zero value on each column, and `formative` must only contain zeros. Some PLS implementations allow `formative` to contain non-zero values, but impose a restriction that the sum of `reflective` and `t(formative)` must satisfy the original restrictions of `reflective`. The only restrictions that `matrixpls` imposes on `inner`, `reflective`, and `formative` is that these must be binary matrices and that the diagonal of `inner` must be zeros.

The argument `W.model` is a ($1 \times k$) matrix that indicates how the indicators are combined to form the composites. The original papers about Partial Least Squares as well as all current PLS implementations define this as `t(reflective) | formative`, which means that the weight pattern must match the model specified in `reflective` and `formative`. `Matrixpls` does not require that `W.model` needs to match `reflective` and `formative`, but accepts any numeric matrix. If this argument is not specified, all elements of `W.model` that correspond to non-zero elements in the `reflective` or `formative` `formative` matrices receive the value 1.

Value

A named numeric vector of class `matrixpls` containing the parameter estimates followed by weights. `matrixpls` returns the following as attributes:

`W` the weight matrix.
`model` the model specification in native format.
`call` the function call.

Additionally, all attributes returned by functions called by `matrixpls` are returned. This can include:

S	the sample covariance matrix.
E	inner weight matrix.
iterations	the number of iterations used by the weight algorithm.
converged	TRUE if the weight algorithm converged and FALSE otherwise.
history	weight optimization history as a matrix.
C	the composite correlation matrix (after disattenuation, if requested).
IC	the indicator-composite covariance matrix (after disattenuation, if requested).
inner	the inner model matrix with estimated parameters.
reflective	the reflective model matrix with estimated parameters.
formative	the formative model matrix with estimated parameters.
Q	the reliability estimates used in disattenuation.
c	the PLS _c loading estimate correction factors.

References

- Rosseel, Y. (2012). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software*, 48(2), 1–36. Retrieved from <http://www.jstatsoft.org/v48/i02>
- Wold, H. (1982). Soft modeling - The Basic Design And Some Extensions. In K. G. Jöreskog & S. Wold (Eds.), *Systems under indirect observation: causality, structure, prediction* (pp. 1–54). Amsterdam: North-Holland.

See Also

Weight algorithms: [weightFun.pls](#); [weightFun.fixed](#); [weightFun.optim](#); [weightFun.principal](#); [weightFun.factor](#)

Weight sign corrections: [weightSign.Wold1985](#); [weightSign.dominantIndicator](#)

Parameter estimators: [parameterEstim.separate](#)

matrixpls-common

Commonly used arguments

Description

The following describes commonly used arguments in the **matrixpls** package.

Arguments

S	Covariance matrix of the data.
model	There are two options for this argument: 1. lavaan script or lavaan parameter table, or 2. a list containing three matrices inner, reflective, and formative defining the free regression paths in the model.
W	Weight matrix, where the indicators are on columns and composites are on the rows.

C	Correlation matrix of the composites.
IC	Correlation matrix of the composites and indicators.
E	Inner weight matrix. A square matrix of inner estimates between the composites.
W.model	A matrix specifying the weight relationships and their starting values.

matrixpls-functions *All estimation function types*

Description

The following describes all estimation function types used in **matrixpls** package.

Arguments

weightFun	A function for calculating indicator weights using the data covariance matrix <i>S</i> , a model specification <i>model</i> , and a weight pattern <i>W.model</i> . Returns a weight matrix <i>W</i> . The default is weightFun.pls
parameterEstim	A function for estimating the model parameters using the data covariance matrix <i>S</i> , model specification <i>model</i> , and weight matrix <i>W</i> . Returns a named vector of parameter estimates. The default is parameterEstim.separate
estimator	A function for estimating the parameters of one model matrix using the data covariance matrix <i>S</i> , a model matrix <i>modelMatrix</i> , and a weight matrix <i>W</i> . Dis-attenuated composite correlation matrix <i>C</i> and indicator composite covariance matrix <i>IC</i> are optional. Returns matrix of parameter estimates. The default is estimator.ols
weightSign	A function for resolving weight sign ambiguity based on the data covariance matrix <i>S</i> and a weight matrix <i>W</i> . Returns a weight matrix <i>W</i> . See weightSign for details.
outerEstim	A function for calculating outer weights using the data covariance matrix <i>S</i> , a weight matrix <i>W</i> , an inner weight matrix <i>E</i> , and a weight pattern <i>W.model</i> . Returns a weight matrix <i>W</i> . See outerEstim .
innerEstim	A function for calculating inner weights using the data covariance matrix <i>S</i> , a weight matrix <i>W</i> , and an inner model matrix <i>inner.mod</i> . Returns an inner weight matrix <i>E</i> . The default is innerEstim.path .
convCheck	A function that takes the old <i>Wold</i> and new weight <i>Wold</i> matrices and returns a scalar that is compared against <i>tol</i> to check for convergence. The default is convCheck.absolute .
optimCrit	A function for calculating value for an optimization criterion based on a <i>matrixpls</i> result object. Returns a scalar. The default is optimCrit.maximizeInnerR2 .
reliabilities	A function for calculating reliability estimates based on the data covariance matrix <i>S</i> , factor loading matrix <i>loadings</i> , and a weight matrix <i>W</i> . Returns a vector of reliability estimates. The default is reliabilityEstim.weightLoadingProduct

`matrixpls.crossvalidate`*Cross-validation of predictions from matrixpls results*

Description

`matrixpls.crossvalidate` Calculates cross-validation predictions using `matrixpls`.

Usage

```
matrixpls.crossvalidate(  
  data,  
  model,  
  ...,  
  predictFun = stats::predict,  
  nGroup = 4,  
  blindfold = FALSE,  
  imputationFun = NULL  
)
```

Arguments

<code>data</code>	Matrix or data frame containing the raw data.
<code>model</code>	There are two options for this argument: 1. lavaan script or lavaan parameter table, or 2. a list containing three matrices <code>inner</code> , <code>reflective</code> , and <code>formative</code> defining the free regression paths in the model.
<code>...</code>	All other arguments are passed through to <code>matrixpls</code> and <code>predictFun</code> .
<code>predictFun</code>	The function used to calculate the predictions.
<code>nGroup</code>	The number of groups to divide the data into.
<code>blindfold</code>	Whether blindfolding should be used instead of holdout sample cross-validation.
<code>imputationFun</code>	The function used to impute missing data before blindfold prediction. If <code>NULL</code> , simple mean substitution is used.

Details

In cross-validation, some elements of the data matrix are set to missing and then predicted based on the remaining observations. The process is repeated until all elements of the data have been predicted.

Cross-validation is typically applied by dividing the data into two groups, the training sample and the validation sample. The prediction model is calculated based on the training sample and used to calculate predictions for the validation sample.

In blindfolding, the data are not omitted case wise, but elements of the data are omitted diagonally. After this, imputation is applied to missing data and the prediction model is calibrated with the dataset containing also the imputations. The imputed values are then predicted with the model.

Value

A matrix containing predictions calculated with cross-validation.

References

Chin, W. W. (2010). How to write up and report PLS analyses. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of partial least squares* (pp. 655–690). Berlin Heidelberg: Springer.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–336). Mahwah, NJ: Lawrence Erlbaum Associates Publishers.

matrixpls.plspm

A plspm compatibility wrapper for matrixpls

Description

matrixpls.plspm mimics plspm function of the plspm package. The arguments and their default values and the output of the function are identical with plspm function, but internally the function uses matrixpls estimation.

Usage

```
matrixpls.plspm(  
  Data,  
  path_matrix,  
  blocks,  
  modes = NULL,  
  scheme = "centroid",  
  scaled = TRUE,  
  tol = 1e-06,  
  maxiter = 100,  
  boot.val = FALSE,  
  br = NULL,  
  dataset = TRUE  
)
```

Arguments

Data	matrix or data frame containing the manifest variables.
path_matrix	A square (lower triangular) boolean matrix representing the inner model (i.e. the path relationships between latent variables).
blocks	list of vectors with column indices or column names from Data indicating the sets of manifest variables forming each block (i.e. which manifest variables correspond to each block).

modes	character vector indicating the type of measurement for each block. Possible values are: "A", "B". The length of modes must be equal to the length of blocks.
scheme	string indicating the type of inner weighting scheme. Possible values are "centroid", "factorial", or "path".
scaled	whether manifest variables should be standardized. When (TRUE, data is scaled to standardized values (mean=0 and variance=1). The variance is calculated dividing by N instead of N-1).
tol	decimal value indicating the tolerance criterion for the iterations (tol=0.000001). Can be specified between 0 and 0.001.
maxiter	integer indicating the maximum number of iterations (maxiter=100 by default). The minimum value of maxiter is 100.
boot.val	whether bootstrap validation should be performed. (FALSE by default).
br	number bootstrap resamples. Used only when boot.val=TRUE. When boot.val=TRUE, the default number of re-samples is 100.
dataset	whether the data matrix used in the computations should be retrieved (TRUE by default).

Details

The function `matrixpls.plspm` calculates indicator weights and estimates a model identically to the `plspm` function. In contrast to the `matrixpls` function that provides only weights and parameter estimates, this function also reports multiple post-estimation statistics. Because of this `matrixpls.plspm` is substantially less efficient than the `matrixpls` function.

The argument `path_matrix` is a matrix of zeros and ones that indicates the structural relationships between composites. This must be a lower triangular matrix. `path_matrix` will contain a 1 when column `j` affects row `i`, 0 otherwise.

Value

An object of class "plspm".

outer_model	Results of the outer model. Includes: outer weights, standardized loadings, communalities, and redundancies
inner_model	Results of the inner (structural) model. Includes: path coeffs and R-squared for each endogenous latent variable
scores	Matrix of latent variables used to estimate the inner model. If scaled=FALSE then scores are latent variables calculated with the original data (non-standardized).
path_coefs	Matrix of path coefficients (this matrix has a similar form as <code>path_matrix</code>)
crossloadings	Correlations between the latent variables and the manifest variables (also called crossloadings)
inner_summary	Summarized results of the inner model. Includes: type of LV, type of measurement, number of indicators, R-squared, average communality, average redundancy, and average variance extracted

effects	Path effects of the structural relationships. Includes: direct, indirect, and total effects
unidim	Results for checking the unidimensionality of blocks (These results are only meaningful for reflective blocks)
gof	Goodness-of-Fit index
data	Data matrix containing the manifest variables used in the model. Only available when dataset=TRUE
boot	List of bootstrapping results; only available when argument boot.val=TRUE

References

Sanchez, G. (2013). *PLS Path Modeling with R*. Retrieved from <http://www.gastonsanchez.com/PLS Path Modeling with R.pdf> #'

Examples

```
cores <- getOption("mc.cores")
options(mc.cores=2)

# Run the example from plsmpm package

# load dataset satisfaction
data(satisfaction)
# inner model matrix
IMAG = c(0,0,0,0,0,0)
EXPE = c(1,0,0,0,0,0)
QUAL = c(0,1,0,0,0,0)
VAL = c(0,1,1,0,0,0)
SAT = c(1,1,1,1,0,0)
LOY = c(1,0,0,0,1,0)
sat_inner = rbind(IMAG, EXPE, QUAL, VAL, SAT, LOY)
# outer model list
sat_outer = list(1:5, 6:10, 11:15, 16:19, 20:23, 24:27)
# vector of modes (reflective indicators)
sat_mod = rep("A", 6)

# apply matrixpls
matrixpls.res <- matrixpls.plspm(satisfaction, sat_inner, sat_outer, sat_mod,
                                scaled=FALSE, boot.val=FALSE)

print(summary(matrixpls.res))

options(mc.cores=cores)
```

matrixpls.sempls *A semPLS compatibility wrapper for matrixpls*

Description

matrixpls.sempls mimics `sempls` function of the `semPLS` package. The arguments and their default values and the output of the function are identical with `sempls` function, but internally the function uses `matrixpls` estimation.

Usage

```
matrixpls.sempls(
  model,
  data,
  maxit = 20,
  tol = 1e-07,
  scaled = TRUE,
  sum1 = FALSE,
  wscheme = "centroid",
  pairwise = FALSE,
  method = c("pearson", "kendall", "spearman"),
  convCrit = c("relative", "square"),
  verbose = TRUE,
  ...
)
```

Arguments

model	An object inheriting from class <code>plsm</code> as returned from <code>plsm</code> or <code>read.splsm</code> .
data	A data.frame containing the observed variables (MVs). The storage mode for all the MVs included in the model must be <code>numeric</code> .
maxit	A numeric value, which determines the maximum number of iterations performed by the PLS algorithm. The default is 20 iterations.
tol	A numeric value, specifying the tolerance for the maximum relative differences in the outer weights. The default value is 10^{-7} .
scaled	A logical value indicating, whether the observed data shall be scaled to zero mean and unit variance. The default is <code>TRUE</code> .
sum1	A logical value indicating, whether the outer weights for each latent variable (LV) shall be standardized to sum up to one. The default is <code>FALSE</code> . Since the factor scores are scaled in each step of the PLS algorithm, changing this value to <code>TRUE</code> does not affect the results.
wscheme	A character naming the weighting scheme to use. Possible values are: <ul style="list-style-type: none"> • "A" or "centroid" for the centroid scheme, the default, • "B" or "factorial" for the factorial scheme and • "C", "pw" or "pathWeighting" for the path weighting scheme.

pairwise	A logical value indicating, whether correlations shall be calculated pairwise. If the observed data does not contain missing values, the results are not affected. The default is FALSE. For more details the R help, ?cor, can be consulted.
method	A character naming the method to calculate the correlations. Possible values are: <ul style="list-style-type: none"> • "pearson", the default, • "kendall", • "spearman". For more details on the method, the R help, ?cor, can be consulted. Note, that despite of the method argument, pearson correlations are always used for the inner approximation (step 2).
convCrit	The convergence criteria to use: <ul style="list-style-type: none"> • "relative", the default, • "square".
verbose	Logical: If FALSE no status messages are printed.
...	Other arguments are ignored

Value

An object of class [sempls](#).

References

Monecke, A., & Leisch, F. (2012). semPLS: Structural Equation Modeling Using Partial Least Squares. *Journal of Statistical Software*, 48(3), 1–32.

See Also

[sempls](#)

Examples

```
if(!require(semPLS)){
  print("This example requires the semPLS package")
} else{
  data(ECSImobi)

  ecsi.sempls <- sempls(model=ECSImobi, data=mobi, wscheme="pathWeighting")
  ecsi <- matrixpls.sempls(model=ECSImobi, data=mobi, wscheme="pathWeighting")

  # If RUnit is installed check that the results are identical

  if(require(RUnit)){
    checkEquals(ecsi.sempls,ecsi, check.attributes = FALSE)
  }

  ecsi
```

```
## create plots
densityplot(ecsi)
densityplot(ecsi, use="prediction")
densityplot(ecsi, use="residuals")

## Values of 'sempls' objects
names(ecsi)
ecsi$outer_weights
ecsi$outer_loadings
ecsi$path_coefficients
ecsi$total_effects

### using convenience methods to sempls results
## path coefficients
pathCoeff(ecsi)

## total effects
totalEffects(ecsi)

## get loadings and check for discriminant validity
(l <- plsLoadings(ecsi))
# outer loadings
print(l, type="outer", digits=2)
# outer loadings greater than 0.5
print(l, type="outer", cutoff=0.5, digits=2)
# cross loadings greater than 0.5
print(l, type="cross", cutoff=0.5, digits=2)

### R-squared
rSquared(ecsi)

}
```

matrixpls.sim

Monte Carlo simulations with matrixpls

Description

Performs Monte Carlo simulations of `matrixpls` with the `sim` function of the `simsem` package. The standard errors and confidence intervals are estimated with the `boot` and `boot.ci` functions of the `boot` package.

Usage

```
matrixpls.sim(
  nRep = NULL,
  model = NULL,
  n = NULL,
```

```

    ...,
    cilevel = 0.95,
    citype = c("norm", "basic", "stud", "perc", "bca"),
    boot.R = 500,
    fitIndices = fitSummary,
    outfundata = NULL,
    outfun = NULL,
    prefun = NULL
  )

```

Arguments

nRep	Number of replications. If any of the n, pmMCAR, or pmMAR arguments are specified as lists, the number of replications will default to the length of the list(s), and nRep need not be specified.
model	There are two options for this argument: 1. lavaan script or lavaan parameter table, or 2. a list containing three matrices inner, reflective, and formative defining the free regression paths in the model.
n	Sample size(s). In single-group models, either a single integer, or a vector of integers to vary sample size across replications. In multigroup models, either a list of single integers (for constant group sizes across replications) or a list of vectors (to vary group sizes across replications). Any non-integers will be rounded.
...	All other arguments are passed through to sim , matrixpls.boot , or matrixpls .
cilevel	Confidence level. This argument will be forwarded to the boot.ci when calculating the confidence intervals.
citype	Type of confidence interval. This argument will be forwarded to the boot.ci when calculating the confidence intervals.
boot.R	Number of bootstrap replications to use to estimate standard errors or FALSE to disable bootstrapping.
fitIndices	A function that returns a list of fit indices for the model. Setting this argument to NULL disables fit indices.
outfundata	A function to be applied to the matrixpls output and the generated data after each replication. Users can get the characteristics of the generated data and also compare the characteristics with the generated output. The output from this function in each replication will be saved in the simulation output (SimResult), and can be obtained using the getExtraOutput function.
outfun	A function to be applied to the matrixpls output at each replication. Output from this function in each replication will be saved in the simulation output (SimResult), and can be obtained using the getExtraOutput function.
prefun	A function to be applied to the dataset before each replication. The output of this function is passed as arguments to matrixpls

Details

This function calls the `sim` function from the `simsem` package to perform Monte Carlo simulations with `matrixpls`. The function parses the model parameters and replaces it with a function call that estimates the model and bootstrapped standard errors and confidence intervals with `matrixpls.boot`.

If the `generate` or `rawdata` arguments are not specified in the `sim` arguments then the `model` argument will be used for data generation and must be specified in `lavaan` format.

Value

An object of class `SimResult-class`.

See Also

`matrixpls`, `matrixpls.boot`, `sim`, `SimResult-class`

Examples

```
if(!require(simsem)){
  print("This example requires the simsem package")
} else{

#
# Runs the second model from
#
# Aguirre-Urreta, M., & Marakas, G. (2013). Partial Least Squares and Models with Formatively
# Specified Endogenous Constructs: A Cautionary Note. Information Systems Research.
# doi:10.1287/isre.2013.0493

library(MASS)

X <- diag(15)
X[upper.tri(X, diag=TRUE)] <- c(
  1.000,
  0.640, 1.000,
  0.640, 0.640, 1.000,
  0.640, 0.640, 0.640, 1.000,
  0.096, 0.096, 0.096, 0.096, 1.000,
  0.096, 0.096, 0.096, 0.096, 0.640, 1.000,
  0.096, 0.096, 0.096, 0.096, 0.640, 0.640, 1.000,
  0.096, 0.096, 0.096, 0.096, 0.640, 0.640, 0.640, 1.000,
  0.115, 0.115, 0.115, 0.115, 0.192, 0.192, 0.192, 0.192, 1.000,
  0.115, 0.115, 0.115, 0.115, 0.192, 0.192, 0.192, 0.192, 0.640, 1.000,
  0.115, 0.115, 0.115, 0.115, 0.192, 0.192, 0.192, 0.192, 0.640, 0.640,
  1.000,
  0.115, 0.115, 0.115, 0.115, 0.192, 0.192, 0.192, 0.192, 0.640, 0.640,
  0.640, 1.000,
  0.000, 0.000, 0.000, 0.000, 0.271, 0.271, 0.271, 0.271, 0.325, 0.325,
  0.325, 0.325, 1.000,
  0.000, 0.000, 0.000, 0.000, 0.271, 0.271, 0.271, 0.271, 0.325, 0.325,
  0.325, 0.325, 0.300, 1.000,
  0.000, 0.000, 0.000, 0.000, 0.271, 0.271, 0.271, 0.271, 0.325, 0.325,
```



```

    0.325, 0.325, 0.300, 0.300, 1.000
  )
  X <- X + t(X) - diag(diag(X))

  colnames(X) <- rownames(X) <- c(paste("Y",1:12,sep=""),paste("X",1:3,sep=""))

  # Print the population covariance matrix X to see that it is correct

  X

  # The estimated model in Lavaan syntax

  analyzeModel <- "
  ksi =~ Y1 + Y2 + Y3 + Y4
  eta1 <~ X1 + X2 + X3
  eta2 =~ Y5 + Y6 + Y7 + Y8
  eta3 =~ Y9 + Y10 + Y11 + Y12

  eta1 ~ ksi
  eta2 ~ eta1
  eta3 ~ eta1
  "

  # Only run 100 replications without bootstrap replications each so that the
  # example runs faster. Generate the data outside simsem because simsem
  # does not support drawing samples from population matrix

  dataSets <- lapply(1:100, function(x){
    mvrnorm(300,          # Sample size
            rep(0,15),   # Means
            X)           # Population covarancematrix
  })

  Output <- matrixpls.sim(model = analyzeModel, rawData = dataSets, boot.R=FALSE,
                          multicore = FALSE, stopOnError = TRUE)

  summary(Output)

}

```

Description

matrixpls.boot is a convenience method that implements bootstrapping of matrixpls with [boot](#) method of the boot package.

Usage

```
matrixpls.boot(
  data,
  model,
  ...,
  R = 500,
  signChange = NULL,
  parallel = c("no", "multicore", "snow"),
  ncpus = getOption("boot.ncpus", 1L),
  dropInadmissible = FALSE,
  stopOnError = FALSE,
  extraFun = NULL
)

## S3 method for class 'matrixplsboot'
summary(object, ..., ci.type = "all")
```

Arguments

<code>data</code>	Matrix or data frame containing the raw data.
<code>model</code>	There are two options for this argument: 1. lavaan script or lavaan parameter table, or 2. a list containing three matrices <code>inner</code> , <code>reflective</code> , and <code>formative</code> defining the free regression paths in the model.
<code>...</code>	All other arguments are passed through to <code>matrixpls</code> and <code>boot</code> .
<code>R</code>	Number of bootstrap samples to draw.
<code>signChange</code>	Sign change correction function.
<code>parallel</code>	The type of parallel operation to be used (if any). If missing, the default is taken from the option <code>"boot.parallel"</code> (and if that is not set, <code>"no"</code>).
<code>ncpus</code>	integer: number of processes to be used in parallel operation: typically one would chose this to the number of available CPUs.
<code>dropInadmissible</code>	A logical indicating whether non-convergent and inadmissible replications should be discarded.
<code>stopOnError</code>	A logical indicating whether bootstrapping should be continued when error occurs in a replication.
<code>extraFun</code>	A function that takes a <code>matrixpls</code> object and a bootstrap sample and returns a numeric vector. The vector is appended to bootstrap replication. Can be used for bootstrapping additional statistics calculated based on the estimation results.
<code>object</code>	object of class <code>matrixplsboot</code>
<code>ci.type</code>	A vector of character strings representing the type of intervals required. Passed on to <code>boot.ci</code> . If <code>"none"</code> , no confidence intervals are calculated.

Value

An object of class `matrixplsboot` and `boot`.

Analyzing the bootstrap results

The output can be analyzed with any of the functions provided by the `boot` package. For example, the `boot.ci` function can be used for calculating confidence intervals and the `empinf` function can be used to calculate influence values that may be useful for identifying outliers.

The class `matrixplsboot` provides only a summary function, which calculates a set of statistics that are commonly of interest after bootstrapping. This includes standard errors, t statistics (estimate / SE) and p-values based on Student's t distribution and standard normal distribution. Because the sampling distribution of the parameter estimates calculated by `matrixpls` are not always known, the p-values cannot be expected to be unbiased.

This concern applies particularly when using PLS weights. Because the PLS literature provides conflicting advice on which probability distribution to use as a reference, the summary method of `matrixplsboot` produces two-tailed p-values based on four different probability distributions. The *regression* p values are based on comparing the t statistic against the references distribution used in regression analysis, namely Student's t distribution with $n - k - 1$ degrees of freedom. The *Hair* p values are based on Hair et al's (2014, p. 134) recommendation to ignore the number of independent variables k and set the degrees of freedom to $n - 1$. The *Henseler* p values are based on the recommendation by Henseler et al (2009, p. 305) that the degrees of freedom should be set as $n + m - 2$, where m is always 1 and n is the number of bootstrap samples. The *z* p values are based on comparing the t statistic against the standard normal distribution. This choice can be motivated by asymptotic normality of the PLS estimates in certain conditions.

References

- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). *A primer on partial least squares structural equations modeling (PLS-SEM)*. Los Angeles: SAGE.
- Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing*, 20, 277–319.
- Rönkkö, M., & Evermann, J. (2013). A critical examination of common beliefs about partial least squares path modeling. *Organizational Research Methods*, 16(3), 425–448. doi: [10.1177/1094428112474693](https://doi.org/10.1177/1094428112474693)
- Rönkkö, M., McIntosh, C. N., & Antonakis, J. (2015). On the adoption of partial least squares in psychological research: Caveat emptor. *Personality and Individual Differences*, (87), 76–84. doi: [10.1016/j.paid.2015.07.019](https://doi.org/10.1016/j.paid.2015.07.019)

See Also

`boot`

Sign change corrections: `signChange.individual`; `signChange.construct`

Examples

```
# Run the customer satisfaction example form plspm

# load dataset satisfaction
data(satisfaction)
# inner model matrix
IMAG = c(0,0,0,0,0,0)
```



```
optimCrit.maximizeFullR2(matrixpls.res)
```

```
optimCrit.gsca(matrixpls.res)
```

Arguments

`matrixpls.res` An object of class `matrixpls` from which the criterion function is calculated

Value

Value of the optimization criterion.

Functions

- `optimCrit.maximizeInnerR2`: maximizes the sum of R2 statistics of the inner matrix
- `optimCrit.maximizeIndicatorR2`: maximizes the sum of R2 statistics of the reflective matrix.
- `optimCrit.maximizeFullR2`: maximizes the sum of R2 statistics of the inner and reflective matrices.
- `optimCrit.gsca`: minimizes the generalized structured component analysis criterion. See [GSCA](#)

See Also

[weightFun.optim](#)

outerEstim

PLS outer estimation

Description

Calculates a set of unstandardized outer weights.

Mode A outer weights are correlations between indicators and composites. Mode B outer weights are regression coefficients of composites on indicators.

For information about GSCA weights, see [GSCA](#).

Usage

```
outerEstim.modeA(S, W, E, W.model, ...)
```

```
outerEstim.modeB(S, W, E, W.model, ...)
```

```
outerEstim.gsca(S, W, E, W.model, model, ...)
```

```
outerEstim.fixed(S, W, E, W.model, ...)
```

Arguments

S	Covariance matrix of the data.
W	Weight matrix, where the indicators are on columns and composites are on the rows.
E	Inner weight matrix. A square matrix of inner estimates between the composites.
W.model	A matrix specifying the weight relationships and their starting values.
...	All other arguments are ignored.
model	There are two options for this argument: 1. lavaan script or lavaan parameter table, or 2. a list containing three matrices inner, reflective, and formative defining the free regression paths in the model.

Value

A matrix of unscaled outer weights W with the same dimensions as W.model.

Functions

- outerEstim.modeA: Mode A outer estimation.
- outerEstim.modeB: Mode B outerestimation.
- outerEstim.gsca: outer estimation with generalized structured component analysis.
- outerEstim.fixed: Fixed weights. Returns the starting weights specified in W.model

References

Lohmöller J.-B. (1989) *Latent variable path modeling with partial least squares*. Heidelberg: Physica-Verlag.

parameterEstim *Parameter estimation of full model*

Description

paramsEstimator functions estimates the statistical model described by model

Usage

```
parameterEstim.separate(
  S,
  model,
  W,
  ...,
  parametersInner = estimator.ols,
  parametersReflective = estimator.ols,
  parametersFormative = estimator.ols,
  disattenuate = FALSE,
  reliabilities = reliabilityEstim.weightLoadingProduct
)
```

Arguments

S	Covariance matrix of the data.
model	There are two options for this argument: 1. lavaan script or lavaan parameter table, or 2. a list containing three matrices <code>inner</code> , <code>reflective</code> , and <code>formative</code> defining the free regression paths in the model.
W	Weight matrix, where the indicators are on columns and composites are on the rows.
...	All other arguments are passed through to <code>parametersInner</code> , <code>parametersReflective</code> , and <code>parametersFormative</code>
<code>parametersInner</code>	A function used to estimate the inner model matrix. The default is estimator.ols
<code>parametersReflective</code>	A function used to estimate the reflective model matrix. The default is estimator.ols
<code>parametersFormative</code>	A function used to estimate the formative model matrix. The default is estimator.ols
<code>disattenuate</code>	If TRUE, C is disattenuated before applying <code>parametersInner</code> .
<code>reliabilities</code>	A function for calculating reliability estimates based on the data covariance matrix S, factor loading matrix loadings, and a weight matrix W. Returns a vector of reliability estimates. The default is reliabilityEstim.weightLoadingProduct

Details

Model can be specified in the lavaan format or the native `matrixpls` format. The native model format is a list of three binary matrices, `inner`, `reflective`, and `formative` specifying the free parameters of a model: `inner` (1×1) specifies the regressions between composites, `reflective` ($k \times 1$) specifies the regressions of observed data on composites, and `formative` ($1 \times k$) specifies the regressions of composites on the observed data. Here k is the number of observed variables and 1 is the number of composites.

If the model is specified in lavaan format, the native format model is derived from this model by assigning all regressions between latent variables to `inner`, all factor loadings to `reflective`, and all regressions of latent variables on observed variables to `formative`. Regressions between observed variables and all free covariances are ignored. All parameters that are specified in the model will be treated as free parameters.

The original papers about Partial Least Squares, as well as many of the current PLS implementations, impose restrictions on the matrices `inner`, `reflective`, and `formative`: `inner` must be a lower triangular matrix, `reflective` must have exactly one non-zero value on each row and must have at least one non-zero value on each column, and `formative` must only contain zeros. Some PLS implementations allow `formative` to contain non-zero values, but impose a restriction that the sum of `reflective` and `t(formative)` must satisfy the original restrictions of `reflective`. The only restrictions that `matrixpls` imposes on `inner`, `reflective`, and `formative` is that these must be binary matrices and that the diagonal of `inner` must be zeros.

Model estimation proceeds as follows. The weights `W` and the data covariance matrix `S` are used to calculate the composite covariance matrix `C` and the indicator-composite covariance matrix `IC`. These are matrices are used to separately estimate each of the three model matrices `inner`, `reflective`,

and formative. This approach of estimating the parameter matrices separately is the standard way of estimation in the PLS literature.

The default estimation approach is to estimate all parameters with a series of OLS regressions using `estimator.ols`.

Value

A named vector of parameter estimates.

`parameterEstim.separate` returns the following as attributes:

C	the composite correlation matrix (after disattenuation, if requested).
IC	the indicator-composite covariance matrix (after disattenuation, if requested).
inner	the inner model matrix with estimated parameters.
reflective	the reflective model matrix with estimated parameters.
formative	the formative model matrix with estimated parameters.
Q	the reliability estimates used in disattenuation.

Additionally, all attributes returned by functions called by `parameterEstim.separate` are returned. This can include:

c	the PLSc loading estimate correction factors.
---	---

Functions

- `parameterEstim.separate`: Estimates the model parameters in inner, reflective, and formative separately.

References

Rosseel, Y. (2012). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software*, 48(2), 1–36. Retrieved from <http://www.jstatsoft.org/v48/i02>

predict.matrixpls *Predict method for matrixpls results*

Description

The `matrixpls` method for the generic function `predict`. Predicts the reflective indicators of endogenous latent variables using estimated model and data for the indicators of exogenous latent variables

Usage

```
## S3 method for class 'matrixpls'
predict(
  object,
  newData,
  predictionType = c("exogenous", "redundancy", "communality", "composites"),
  means = NULL,
  ...
)
```

Arguments

object	matrixpls estimation result object produced by the <code>matrixpls</code> function.
newData	A data frame or a matrix containing data used for prediction.
predictionType	"exogenous" (default) predicts indicators from exogenous composites. "redundancy" and "communality" are alternative strategies described by Chin (2010). "composites" returns the composites calculated by multiplying the data with the weight matrix.
means	A vector of means of the original data used to calculate intercepts for the linear prediction equations. If not provided, calculated from the new data or assumed zero.
...	All other arguments are ignored.

Value

a matrix of predicted values for reflective indicators of endogenous latent variables or weighted composites of the indicators.

References

Wold, H. (1974). Causal flows with latent variables: Partings of the ways in the light of NIPALS modeling. *European Economic Review*, 5(1), 67–86. doi: [10.1016/00142921\(74\)900087](https://doi.org/10.1016/00142921(74)900087)

Chin, W. W. (2010). How to write up and report PLS analyses. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of partial least squares* (pp. 655–690). Berlin Heidelberg: Springer.

See Also

Other post-estimation functions: `ave()`, `cei()`, `cr()`, `effects.matrixpls()`, `fitSummary()`, `fitted.matrixpls()`, `gof()`, `htmt()`, `loadings()`, `r2()`, `residuals.matrixpls()`

Examples

```
# Run the customer satisfaction example from plsmpm

# load dataset satisfaction
data(satisfaction)
# inner model matrix
```

```

IMAG = c(0,0,0,0,0,0)
EXPE = c(1,0,0,0,0,0)
QUAL = c(0,1,0,0,0,0)
VAL = c(0,1,1,0,0,0)
SAT = c(1,1,1,1,0,0)
LOY = c(1,0,0,0,1,0)
inner = rbind(IMAG, EXPE, QUAL, VAL, SAT, LOY)
colnames(inner) <- rownames(inner)

# Reflective model

reflective<- matrix(
  c(1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
    0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
    0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
    0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0,
    0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0,
    0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1),
  27,6, dimnames = list(colnames(satisfaction)[1:27],colnames(inner)))

# empty formative model

formative <- matrix(0, 6, 27, dimnames = list(colnames(inner),
                                             colnames(satisfaction)[1:27]))

satisfaction.model <- list(inner = inner,
                          reflective = reflective,
                          formative = formative)

# Estimation using covariance matrix

satisfaction.out <- matrixpls(cov(satisfaction[,1:27]),
                              model = satisfaction.model)

print(satisfaction.out)

# Predict indicators using means from the data
predict(satisfaction.out,
        newData = satisfaction,
        means= sapply(satisfaction, mean))

# Calculate composite scores
predict(satisfaction.out,
        newData = satisfaction,
        predictionType = "composites")

```

Description

Calculates Q2 predictive relevance statistics based on comparing predictions and real data.

Usage

```
q2(originalData, predictedData, model = NULL)
```

Arguments

<code>originalData</code>	A matrix or a data.frame containing the original data.
<code>predictedData</code>	A matrix or a data.frame containing the predicted data that are compared against the original data to calculate the predictive relevance statistic.
<code>model</code>	There are two options for this argument: 1. lavaan script or lavaan parameter table, or 2. a list containing three matrices <code>inner</code> , <code>reflective</code> , and <code>formative</code> defining the free regression paths in the model.

Details

The Q2 statistic is calculated as $1 - sse/sso$ where `sse` is the sum of squared prediction errors based on comparison of the `originalData` and `predictedData` and `sso` is based on prediction with mean. If the predicted data contain the `groups` attribute, which indicates the groups used in blindfolding or cross-validation, the means are calculated separately for each group excluding the predicted group from the calculation.

Value

A list with `total`, `block`, and `indicator` elements containing the Q2 predictive relevance statistics for the full dataset, for each indicator block, and for each indicator

<code>r2</code>	<i>R2 for matrixpls results</i>
-----------------	---------------------------------

Description

The `matrixpls` method for the generic function `r2` computes the squared multiple correlation (R2) for composites predicted by other composites in the model.

Usage

```
r2(object, ...)
```

Arguments

<code>object</code>	matrixpls estimation result object produced by the <code>matrixpls</code> function.
<code>...</code>	All other arguments are ignored.

Value

A named numeric vector containing the R2 values.

See Also

Other post-estimation functions: `ave()`, `cei()`, `cr()`, `effects.matrixpls()`, `fitSummary()`, `fitted.matrixpls()`, `gof()`, `htmt()`, `loadings()`, `predict.matrixpls()`, `residuals.matrixpls()`

reliabilityEstim	<i>Reliabilities as products of weights and loadings</i>
------------------	--

Description

Calculates reliabilities as a matrix product of loadings and weights.

Usage

```
reliabilityEstim.weightLoadingProduct(S, loadings, W, ...)
```

```
reliabilityEstim.alpha(S, loadings, W, ...)
```

Arguments

S	the data covariance matrix
loadings	matrix of factor loading estimates
W	matrix of weights
...	All other arguments are ignored.

Value

a named vector of estimated composite reliabilities.

Functions

- `reliabilityEstim.weightLoadingProduct`: Reliability estimation based on weights and loadings.
- `reliabilityEstim.alpha`: Reliability estimation with Cronbach's alpha

residuals.matrixpls *Residual diagnostics for matrixpls results*

Description

The `matrixpls` method for generic function `residuals` computes the residual covariance matrix and various fit indices.

Usage

```
## S3 method for class 'matrixpls'
residuals(object, ..., observed = TRUE)
```

Arguments

<code>object</code>	matrixpls estimation result object produced by the <code>matrixpls</code> function.
<code>...</code>	All other arguments are ignored.
<code>observed</code>	If TRUE (default) the observed residuals from the <code>outerEstim.model</code> regressions (indicators regressed on composites) are returned. If FALSE, the residuals are calculated by combining inner, reflective, and formative as a simultaneous equations system and subtracting the covariances implied by this system from the observed covariances. The error terms are constrained to be uncorrelated and covariances between exogenous observed values are fixed at their sample values.

Details

The residuals can be either observed residuals from the regressions of indicators on composites and composites on composites (i.e. the reflective and inner models) as presented by Lohmöller (1989, ch 2.4) or model implied residuals calculated by subtracting model implied covariance matrix from the sample covariance matrix as done by Henseler et al. (2014).

The root mean squared residual indices (Lohmöller, 1989, eq 2.118) are calculated from the off diagonal elements of the residual covariance matrix. The standardized root mean squared residual (SRMR) is calculated based on the standardized residuals of the reflective model matrix.

Following Hu and Bentler (1999, Table 1), the SRMR index is calculated by dividing with $p(p + 1)/2$, where p is the number of indicator variables. In typical SEM applications, the diagonal of residual covariance matrix consists of all zeros because error term variances are freely estimated. To make the SRMR more comparable with the index produced by SEM software, the SRMR is calculated by summing only the squares of off-diagonal elements, which is equivalent to including a diagonal of all zeros.

Two versions of the SRMR index are provided, the traditional SRMR that includes all residual covariances, and the version proposed by Henseler et al. (2014) where the within-block residual covariances are ignored.

Value

A list with three elements: inner, outer, and indices elements containing the residual covariance matrix of regressions of composites on other composites, the residual covariance matrix of indicators on composites, and various indices calculated based on the residuals.

References

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., ... Calantone, R. J. (2014). Common Beliefs and Reality About PLS Comments on Rönkkö and Evermann (2013). *Organizational Research Methods*, 17(2), 182–209. doi: [10.1177/1094428114526928](https://doi.org/10.1177/1094428114526928)

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55.

Lohmöller J.-B. (1989) *Latent variable path modeling with partial least squares*. Heidelberg: Physica-Verlag.

See Also

Other post-estimation functions: [ave\(\)](#), [cei\(\)](#), [cr\(\)](#), [effects.matrixpls\(\)](#), [fitSummary\(\)](#), [fitted.matrixpls\(\)](#), [gof\(\)](#), [htmt\(\)](#), [loadings\(\)](#), [predict.matrixpls\(\)](#), [r2\(\)](#)

satisfaction

Satisfaction dataset

Description

This data set contains the variables from a customer satisfaction study of a Spanish credit institution on 250 customers. Adopted from the orphaned plspm package.

Usage

satisfaction

Format

A data frame with 250 observations and 28 variables. Variables from 1 to 27 refer to six latent concepts: 1) IMAG=Image, 2) EXPE=Expectations, 3) QUAL=Quality, 4) VAL=Value, 5) SAT=Satisfaction, and 6) LOY=Loyalty. The last variable is a categorical variable indicating the gender of the individual.

IMAG: Includes variables such as reputation, trustworthiness, seriousness, solidness, and caring about customer's needs.

EXPE: Includes variables such as products and services provided, customer service, providing solutions, and expectations for the overall quality.

QUAL: Includes variables such as reliable products and services, range of products and services, personal advice, and overall perceived quality.

VAL: Includes variables such as beneficial services and products, valuable investments, quality relative to price, and price relative to quality.

SAT: Includes variables such as overall rating of satisfaction, fulfillment of expectations, satisfaction relative to other banks, and performance relative to customer's ideal bank.

LOY: Includes variables such as propensity to choose the same bank again, propensity to switch to other bank, intention to recommend the bank to friends, and sense of loyalty.

Source

Laboratory of Information Analysis and Modeling (LIAM). Facultat d'Informatica de Barcelona, Universitat Politecnica de Catalunya.

Examples

```
data(satisfaction)
satisfaction
```

signChange

Sign change corrections for bootstrap

Description

These functions selectively reverse the signs of the weights in bootstrap samples to be consistent with the weights calculated based on the original sample.

Usage

```
signChange.individual(Worig, W)
```

```
signChange.construct(Worig, W)
```

Arguments

Worig	The original weight matrix.
W	a Weight matrix of a bootstrap sample.

Details

Sign change corrections are a controversial and inconsistently implemented feature in PLS analysis. The two corrections described in the literature are the individual sign change correction and the construct level sign change corrections. The individual correction changes the signs of W to match Worig.

The construct level correction changes the signs of W on all rows where the sign of the sum of the row differs between Worig and W.

The sign change corrections are described ambiguously and sometimes implemented inconsistently between software. **matrixpls** implements the corrections by adjusting the weights before calculating parameter estimates in each bootstrap replication. Some software implement the correction

post-hoc by adjusting the bootstrap estimates directly. Moreover, the literature present at least two different formulas for the construct level correction. **matrixpls** implements the version described by Tenenhaus et al. (2005).

The sign change corrections should not be confused with sign indeterminacy corrections applied to individual analyses (See [weightSign](#)).

Value

A weight matrix with the same dimensions as W after applying the correction.

Functions

- `signChange.individual`: individual sign change correction
- `signChange.construct`: individual sign change correction

References

Tenenhaus, M., Esposito Vinzi, V., Chatelin, Y.-M., & Lauro, C. (2005). PLS Path Modeling. *Computational Statistics & Data Analysis*, 48(1), 159–205. doi: [10.1016/j.csda.2004.03.005](https://doi.org/10.1016/j.csda.2004.03.005)

Rönkkö, M., McIntosh, C. N., & Antonakis, J. (2015). On the adoption of partial least squares in psychological research: Caveat emptor. *Personality and Individual Differences*, (87), 76–84. doi: [10.1016/j.paid.2015.07.019](https://doi.org/10.1016/j.paid.2015.07.019)

See Also

[matrixpls.boot](#)

weightFun

Indicator weight algorithms

Description

Estimates a weight matrix using Partial Least Squares or a related algorithm.

`weightFun.factor` calculates weights by estimating a common factor analysis model with a single factor for each indicator block and using the resulting estimates to calculate factor score weights

`weightFun.principal` calculates weights by calculating a principal component analysis for each indicator block and returning the weights for the first principal component.

Usage

```
weightFun.pls(
  S,
  model,
  W.model,
  outerEstim = NULL,
  innerEstim = innerEstim.path,
```



```

    ...,
    convCheck = convCheck.absolute,
    variant = "lohmoller",
    tol = 1e-05,
    iter = 100,
    validateInput = TRUE
)

weightFun.optim(
  S,
  model,
  W.model,
  parameterEstim = parameterEstim.separate,
  optimCrit = optimCrit.maximizeInnerR2,
  method = "BFGS",
  ...,
  validateInput = TRUE,
  standardize = TRUE
)

weightFun.fixed(S, model, W.model = NULL, ..., standardize = TRUE)

weightFun.factor(
  S,
  model,
  W.model = NULL,
  ...,
  fm = "minres",
  standardize = TRUE
)

weightFun.principal(S, model, W.model = NULL, ..., standardize = TRUE)

```

Arguments

S	Covariance matrix of the data.
model	There are two options for this argument: 1. lavaan script or lavaan parameter table, or 2. a list containing three matrices <code>inner</code> , <code>reflective</code> , and <code>formative</code> defining the free regression paths in the model.
W.model	A matrix specifying the weight relationships and their starting values.
outerEstim	A function or a list of functions used for outer estimation. If the value of this parameter is a function, the same function is applied to all composites. If the value is a list, the composite <code>n</code> is estimated with the estimator in the <code>n</code> th position in the list. If this argument is <code>NULL</code> the <code>outerEstim.modeA</code> is used for all composites that are linked to at least one indicator in the reflective matrix. <code>outerEstim.modeB</code> is used for all other composites. See <code>outerEstim</code> .
innerEstim	A function for calculating inner weights using the data covariance matrix <code>S</code> , a weight matrix <code>W</code> , and an inner model matrix <code>inner.mod</code> . Returns an inner weight

	matrix E. The default is <code>innerEstim.path</code> .
...	All other arguments are passed through to other estimation functions.
<code>convCheck</code>	A function that takes the old Wold and new weight Wold matrices and returns a scalar that is compared against <code>tol</code> to check for convergence. The default is <code>convCheck.absolute</code> .
<code>variant</code>	Choose either Lohmöller's ("lohmoeller", default) or Wold's ("wold") variant of PLS. In Wold's variant the inner and outer estimation steps are repeated for each indicator block whereas in Lohmöller's variant the weights for all composites are calculated simultaneously.
<code>tol</code>	Decimal value indicating the tolerance criterion for convergence.
<code>iter</code>	An integer indicating the maximum number of iterations.
<code>validateInput</code>	A boolean indicating whether the validity of the parameter values should be tested.
<code>parameterEstim</code>	A function for estimating the model parameters using the data covariance matrix S, model specification <code>model</code> , and weight matrix W. Returns a named vector of parameter estimates. The default is <code>parameterEstim.separate</code>
<code>optimCrit</code>	A function for calculating value for an optimization criterion based on a <code>matrixpls</code> result object. Returns a scalar. The default is <code>optimCrit.maximizeInnerR2</code> .
<code>method</code>	The minimization algorithm to be used. See <code>optim</code> for details. Default is "BFGS".
<code>standardize</code>	A boolean indicating whether S the weights should be scaled to produce standardized composites.
<code>fm</code>	factoring method for estimating the common factor model. Possible values are <code>minres</code> , <code>wls</code> , <code>gls</code> , <code>pa</code> , and <code>ml</code> . The parameter is passed through to <code>fa</code> .

Details

Model can be specified in the lavaan format or the native `matrixpls` format. The native model format is a list of three binary matrices, `inner`, `reflective`, and `formative` specifying the free parameters of a model: `inner` (1×1) specifies the regressions between composites, `reflective` ($k \times 1$) specifies the regressions of observed data on composites, and `formative` ($1 \times k$) specifies the regressions of composites on the observed data. Here k is the number of observed variables and 1 is the number of composites.

If the model is specified in lavaan format, the native format model is derived from this model by assigning all regressions between latent variables to `inner`, all factor loadings to `reflective`, and all regressions of latent variables on observed variables to `formative`. Regressions between observed variables and all free covariances are ignored. All parameters that are specified in the model will be treated as free parameters.

The original papers about Partial Least Squares, as well as many of the current PLS implementations, impose restrictions on the matrices `inner`, `reflective`, and `formative`: `inner` must be a lower triangular matrix, `reflective` must have exactly one non-zero value on each row and must have at least one non-zero value on each column, and `formative` must only contain zeros. Some PLS implementations allow `formative` to contain non-zero values, but impose a restriction that the sum of `reflective` and `t(formative)` must satisfy the original restrictions of `reflective`. The

only restrictions that `matrixpls` imposes on `inner`, `reflective`, and `formative` is that these must be binary matrices and that the diagonal of `inner` must be zeros.

The argument `W.model` is a $(1 \times k)$ matrix that indicates how the indicators are combined to form the composites. The original papers about Partial Least Squares as well as all current PLS implementations define this as `t(reflective) | formative`, which means that the weight pattern must match the model specified in `reflective` and `formative`. `Matrixpls` does not require that `W.model` needs to match `reflective` and `formative`, but accepts any numeric matrix. If this argument is not specified, all elements of `W.model` that correspond to non-zero elements in the `reflective` or `formative` matrices receive the value 1.

`weightFun.pls` calculates indicator weights by calling the `innerEstim` and `outerEstim` iteratively until either the convergence criterion or maximum number of iterations is reached and provides the results in a matrix.

`weightFun.optim` calculates indicator weights by optimizing the indicator weights against the criterion function using `optim`. The algorithm works by first estimating the model with the starting weights. The resulting `matrixpls` object is passed to the `optimCrit` function, which evaluates the optimization criterion for the weights. The weights are adjusted and new estimates are calculated until the optimization criterion converges.

Value

An object of class "matrixplsweights", which is a matrix containing the weights with the following attributes:

<code>iterations</code>	Number of iterations performed
<code>converged</code>	A boolean indicating if the algorithm converged
<code>history</code>	A data.frame containing the weights for each iteration

`weightFun.pls` returns the following as attributes:

<code>S</code>	the sample covariance matrix.
<code>E</code>	inner weight matrix.
<code>iterations</code>	the number of iterations used by the weight algorithm.
<code>converged</code>	TRUE if the weight algorithm converged and FALSE otherwise.
<code>history</code>	weight optimization history as a matrix.

Functions

- `weightFun.pls`: partial Least Squares and other iterative two-stage weight algorithms.
- `weightFun.optim`: calculates a set of weights to minimize an optimization criterion.
- `weightFun.fixed`: returns the starting weights.
- `weightFun.factor`: blockwise factor score weights.
- `weightFun.principal`: blockwise principal component weights.

References

RosseeL, Y. (2012). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software*, 48(2), 1–36. Retrieved from <http://www.jstatsoft.org/v48/i02>

Examples

```

# Run the customer satisfaction example from plsppm

# load dataset satisfaction
data(satisfaction)
# inner model matrix
IMAG = c(0,0,0,0,0,0)
EXPE = c(1,0,0,0,0,0)
QUAL = c(0,1,0,0,0,0)
VAL = c(0,1,1,0,0,0)
SAT = c(1,1,1,1,0,0)
LOY = c(1,0,0,0,1,0)
inner = rbind(IMAG, EXPE, QUAL, VAL, SAT, LOY)
colnames(inner) <- rownames(inner)

# Reflective model
list(1:5, 6:10, 11:15, 16:19, 20:23, 24:27)

reflective<- matrix(
  c(1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
    0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
    0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
    0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
    0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0,
    0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1),
  27,6, dimnames = list(colnames(satisfaction)[1:27],colnames(inner)))

# empty formative model

formative <- matrix(0, 6, 27, dimnames = list(colnames(inner), colnames(satisfaction)[1:27]))

# Estimation using covariance matrix
model <- list(inner = inner,
              reflective = reflective,
              formative = formative)

S <- cov(satisfaction[,1:27])

matrixpls.ModeA <- matrixpls(S, model)
matrixpls.ModeB <- matrixpls(S, model, outerEstim = outerEstim.modeB)
matrixpls.MaxR2 <- matrixpls(S, model, weightFun = weightFun.optim)

# Compare the R2s from the different estimations

R2s <- cbind(r2(matrixpls.ModeA), r2(matrixpls.ModeB), r2(matrixpls.MaxR2))
print(R2s)
apply(R2s,2,mean)

# Optimization against custom function

maximizeSumOfCorrelations <- function(matrixpls.res){
  C <- attr(matrixpls.res,"C")

```

```

    model <- attr(matrixpls.res,"model")
    - sum(C[model$inner != 0])
  }

matrixpls.MaxCor <- matrixpls(S, model, weightFun = weightFun.optim,
                             optimCrit = maximizeSumOfCorrelations)

# Compare the Mode B and optimized solutions

C <- attr(matrixpls.ModeB,"C")
print(C)
print(sum(C[inner != 0]))
C <- attr(matrixpls.MaxCor,"C")
print(C)
print(sum(C[inner != 0]))

```

weightSign

Sign ambiguity corrections

Description

Sign ambiguity corrections adjust the signs of the weights to satisfy a criterion.

Usage

```
weightSign.Wold1985(W, S)
```

```
weightSign.dominantIndicator(W, S)
```

Arguments

W	Weight matrix, where the indicators are on columns and composites are on the rows.
S	Covariance matrix of the data.

Details

Instead of fixing a weight to a particular value, composite variables are typically provided a scale by standardization. This leads to sign indeterminacy because standardized weights W and $-W$ both satisfy the scaling constraint. The sign ambiguity corrections add additional constraints that make

The sign indeterminacy corrections should not be confused with sign chance corrections applied to bootstrap samples (See [signChange](#)).

Value

W after sign correction.

Functions

- `weightSign.Wold1985`: Adjust the signs of W so that the majority of the indicators are positively correlated with the composite as proposed by Wold (1985).
- `weightSign.dominantIndicator`: Adjust the signs of W so that the first indicator of each composite has positive weight.

References

Wold, H. (1985). Partial Least Squares. In S. Kotz & N. L. Johnson (Eds.), Encyclopedia of statistical sciences (Vol. 6, pp. 581–591). New York: Wiley.

See Also

[matrixpls](#);

Index

- * **Weight algorithms**
 - weightFun, 48
- * **datasets**
 - satisfaction, 46
- * **post-estimation functions**
 - ave, 5
 - cei, 6
 - cr, 8
 - effects.matrixpls, 9
 - fitSummary, 13
 - fitted.matrixpls, 14
 - gof, 14
 - htmt, 17
 - loadings, 19
 - predict.matrixpls, 40
 - r2, 43
 - residuals.matrixpls, 45
- _PACKAGE (matrixpls-package), 3
- ave, 5, 6, 8, 9, 13–15, 18, 20, 41, 44, 46
- boot, 30, 33–35
- boot.ci, 30, 31, 34, 35
- cei, 6, 6, 8, 9, 13–15, 18, 20, 41, 44, 46
- convCheck, 7
- convCheck.absolute, 23, 50
- cr, 6, 8, 9, 13–15, 18, 20, 41, 44, 46
- effects, 9
- effects.matrixpls, 6, 8, 9, 13–15, 18, 20, 41, 44, 46
- empinf, 35
- estimator, 9
- estimator.ols, 23, 39, 40
- estimator.plsreg, 10
- fa, 10, 11, 50
- fitSummary, 6, 8, 9, 13, 14, 15, 18, 20, 41, 44, 46
- fitted.matrixpls, 6, 8, 9, 13, 14, 15, 18, 20, 41, 44, 46
- gof, 6, 8, 9, 13, 14, 14, 18, 20, 41, 44, 46
- GSCA, 15, 19, 37
- htmt, 6, 8, 9, 13–15, 17, 20, 41, 44, 46
- innerEstim, 18
- innerEstim.gsca, 15
- innerEstim.path, 23, 50
- lavaan, 11
- loadings, 6, 8, 9, 13–15, 18, 19, 41, 44, 46
- matrixpls, 3, 5, 6, 8, 9, 13, 14, 17, 19, 20, 24, 26, 30–32, 34, 41, 43, 45, 54
- matrixpls-common, 22
- matrixpls-functions, 23
- matrixpls-package, 3
- matrixpls.boot, 31, 32, 48
- matrixpls.boot (matrixplsboot), 33
- matrixpls.crossvalidate, 24
- matrixpls.plspm, 25
- matrixpls.sempls, 28
- matrixpls.sim, 30
- matrixplsboot, 33
- optim, 50, 51
- optimCrit, 36
- optimCrit.gsca, 15
- optimCrit.maximizeInnerR2, 23, 50
- outerEstim, 23, 37, 49
- outerEstim.gsca, 15
- outerEstim.modeA, 49
- outerEstim.modeB, 49
- parameterEstim, 38
- parameterEstim.separate, 10, 20, 22, 23, 50
- plsm, 28

`predict.matrixpls`, [6](#), [8](#), [9](#), [13–15](#), [18](#), [20](#),
[40](#), [44](#), [46](#)

`q2`, [42](#)

`r2`, [6](#), [8](#), [9](#), [13–15](#), [18](#), [20](#), [41](#), [43](#), [46](#)

`read.splsm`, [28](#)

`reliabilityEstim`, [44](#)

`reliabilityEstim.weightLoadingProduct`,
[23](#), [39](#)

`residuals.matrixpls`, [6](#), [8](#), [9](#), [13–15](#), [18](#), [20](#),
[41](#), [44](#), [45](#)

`satisfaction`, [46](#)

`sempls`, [28](#), [29](#)

`signChange`, [47](#), [53](#)

`signChange.construct`, [35](#)

`signChange.individual`, [35](#)

`sim`, [30–32](#)

`summary.matrixplsboot (matrixplsboot)`,
[33](#)

`weightFun`, [48](#)

`weightFun.factor`, [22](#)

`weightFun.fixed`, [22](#)

`weightFun.optim`, [15](#), [22](#), [37](#)

`weightFun.pls`, [15](#), [20](#), [22](#), [23](#)

`weightFun.principal`, [22](#)

`weightSign`, [20](#), [23](#), [48](#), [53](#)

`weightSign.dominantIndicator`, [22](#)

`weightSign.Wold1985`, [22](#)