

# Package ‘semTools’

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**Type** Package

**Title** Useful tools for structural equation modeling.

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**Depends** R(>= 2.14), MASS, lavaan, methods

**Suggests** parallel, Amelia, mice, foreign

**Description** This package provide useful tools for structural equation modeling analysis.

**License** GPL (>= 2)

**LazyLoad** yes

**LazyData** yes

**URL** <https://github.com/simsem/semTools/wiki>

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dat2way

*Simulated Dataset to Demonstrate Two-way Latent Interaction*

---

## Description

A simulated data set with 2 independent factors and 1 dependent factor where each factor has three indicators

## Usage

```
data(dat2way)
```

## Format

A data frame with 500 observations of 9 variables.

- x1** The first indicator of the first independent factor
- x2** The second indicator of the first independent factor
- x3** The third indicator of the first independent factor
- x4** The first indicator of the second independent factor
- x5** The second indicator of the second independent factor
- x6** The third indicator of the second independent factor
- x7** The first indicator of the dependent factor
- x8** The second indicator of the dependent factor
- x9** The third indicator of the dependent factor

## Source

Data was generated by the [mvrnorm](#) function in the MASS package.

## Examples

```
head(dat2way)
```

---

dat3way*Simulated Dataset to Demonstrate Three-way Latent Interaction*

---

**Description**

A simulated data set with 3 independent factors and 1 dependent factor where each factor has three indicators

**Usage**

```
data(dat3way)
```

**Format**

A data frame with 500 observations of 12 variables.

**x1** The first indicator of the first independent factor

**x2** The second indicator of the first independent factor

**x3** The third indicator of the first independent factor

**x4** The first indicator of the second independent factor

**x5** The second indicator of the second independent factor

**x6** The third indicator of the second independent factor

**x7** The first indicator of the third independent factor

**x8** The second indicator of the third independent factor

**x9** The third indicator of the third independent factor

**x10** The first indicator of the dependent factor

**x11** The second indicator of the dependent factor

**x12** The third indicator of the dependent factor

**Source**

Data was generated by the [mvrnorm](#) function in the MASS package.

**Examples**

```
head(dat3way)
```

---

exLong	<i>Simulated Data set to Demonstrate Longitudinal Measurement Invariance</i>
--------	--

---

### Description

A simulated data set with 1 factors with 3 indicators in three timepoints

### Usage

```
data(exLong)
```

### Format

A data frame with 200 observations of 10 variables.

**sex** Sex of respondents

**y1t1** Indicator 1 in Time 1

**y2t1** Indicator 2 in Time 1

**y3t1** Indicator 3 in Time 1

**y1t2** Indicator 1 in Time 2

**y2t2** Indicator 2 in Time 2

**y3t2** Indicator 3 in Time 2

**y1t3** Indicator 1 in Time 3

**y2t3** Indicator 2 in Time 3

**y3t3** Indicator 3 in Time 3

### Source

Data was generated using the `simsem` package.

### Examples

```
head(exLong)
```

---

findRMSEApower	<i>Find the statistical power based on population RMSEA</i>
----------------	---

---

### Description

Find the proportion of the samples from the sampling distribution of RMSEA in the alternative hypothesis rejected by the cutoff derived from the sampling distribution of RMSEA in the null hypothesis. This function can be applied for both test of close fit and test of not-close fit (MacCallum, Browne, & Suguwara, 1996)

### Usage

```
findRMSEApower(rmseao, rmseaA, df, n, alpha=.05, group=1)
```

**Arguments**

rmsea0	Null RMSEA
rmseaA	Alternative RMSEA
df	Model degrees of freedom
n	Sample size of a dataset
alpha	Alpha level used in power calculations
group	The number of group that is used to calculate RMSEA.

**Details**

This function find the proportion of sampling distribution derived from the alternative RMSEA that is in the critical region derived from the sampling distribution of the null RMSEA. If `rmseaA` is greater than `rmsea0`, the test of close fit is used and the critical region is in the right hand side of the null sampling distribution. On the other hand, if `rmseaA` is less than `rmsea0`, the test of not-close fit is used and the critical region is in the left hand side of the null sampling distribution (MacCallum, Browne, & Suguwara, 1996).

**Author(s)**

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

**References**

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, 1, 130-149.

**See Also**

- [plotRMSEApower](#) to plot the statistical power based on population RMSEA given the sample size
- [plotRMSEAdist](#) to visualize the RMSEA distributions
- [findRMSEAsamplesize](#) to find the minium sample size for a given statistical power based on population RMSEA

**Examples**

```
findRMSEApower(rmsea0=.05, rmseaA=.08, df=20, n=200)
```

---

findRMSEAsamplesize	<i>Find the minimum sample size for a given statistical power based on population RMSEA</i>
---------------------	---

---

**Description**

Find the minimum sample size for a specified statistical power based on population RMSEA. This function can be applied for both test of close fit and test of not-close fit (MacCallum, Browne, & Suguwara, 1996)

## Usage

```
findRMSEAsamplesize(rmse0, rmseaA, df, power=0.80, alpha=.05, group=1)
```

## Arguments

rmse0	Null RMSEA
rmseaA	Alternative RMSEA
df	Model degrees of freedom
power	Desired statistical power to reject misspecified model (test of close fit) or retain good model (test of not-close fit)
alpha	Alpha level used in power calculations
group	The number of group that is used to calculate RMSEA.

## Details

This function find the minimum sample size for a specified power based on an iterative routine. The sample size keep increasing until the calculated power from [findRMSEApower](#) function is just over the specified power. If group is greater than 1, the resulting sample size is the sample size per group.

## Author(s)

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

## References

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, 1, 130-149.

## See Also

- [plotRMSEApower](#) to plot the statistical power based on population RMSEA given the sample size
- [plotRMSEAdist](#) to visualize the RMSEA distributions
- [findRMSEApower](#) to find the statistical power based on population RMSEA given a sample size

## Examples

```
findRMSEAsamplesize(rmse0=.05, rmseaA=.08, df=20, power=0.80)
```

---

indProd	<i>Make products of indicators using no centering, mean centering, double-mean centering, or residual centering</i>
---------	---

---

### Description

The indProd function will make products of indicators using no centering, mean centering, double-mean centering, or residual centering. The orthogonalize function is the shortcut of the indProd function to make the residual-centered indicators products.

### Usage

```
indProd(data, var1, var2, var3=NULL, match = TRUE, meanC = TRUE,
residualC = FALSE, doubleMC = TRUE, namesProd = NULL)
orthogonalize(data, var1, var2, var3=NULL, match=TRUE, namesProd=NULL)
```

### Arguments

data	The desired data to be transformed.
var1	Names or indices of the variables loaded on the first factor
var2	Names or indices of the variables loaded on the second factor
var3	Names or indices of the variables loaded on the third factor (for three-way interaction)
match	Specify TRUE to use match-paired approach (Marsh, Wen, & Hau, 2004). If FALSE, the resulting products are all possible products.
meanC	Specify TRUE for mean centering the main effect indicator before making the products
residualC	Specify TRUE for residual centering the products by the main effect indicators (Little, Bovaird, & Widaman, 2006).
doubleMC	Specify TRUE for centering the resulting products (Lin et. al., 2010)
namesProd	The names of resulting products

### Value

The original data attached with the products.

### Author(s)

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>) Alex Schoemann (University of Kansas; <schoemann@ku.edu>)

### References

- Marsh, H. W., Wen, Z. & Hau, K. T. (2004). Structural equation models of latent interactions: Evaluation of alternative estimation strategies and indicator construction. *Psychological Methods*, 9, 275-300.
- Lin, G. C., Wen, Z., Marsh, H. W., & Lin, H. S. (2010). Structural equation models of latent interactions: Clarification of orthogonalizing and double-mean-centering strategies. *Structural Equation Modeling*, 17, 374-391.

Little, T. D., Bovaird, J. A., & Widaman, K. F. (2006). On the merits of orthogonalizing powered and product terms: Implications for modeling interactions among latent variables. *Structural Equation Modeling*, 13, 497-519.

### See Also

- [probe2WayMC](#) For probing the two-way latent interaction when the results are obtained from mean-centering, or double-mean centering.
- [probe3WayMC](#) For probing the three-way latent interaction when the results are obtained from mean-centering, or double-mean centering.
- [probe2WayRC](#) For probing the two-way latent interaction when the results are obtained from residual-centering approach.
- [probe3WayRC](#) For probing the two-way latent interaction when the results are obtained from residual-centering approach.
- [plotProbe](#) Plot the simple intercepts and slopes of the latent interaction.

### Examples

```
# Mean centering / two-way interaction / match-paired
dat <- indProd(attitude[,-1], var1=1:3, var2=4:6)

# Residual centering / two-way interaction / match-paired
dat2 <- indProd(attitude[,-1], var1=1:3, var2=4:6, match=FALSE, meanC=FALSE, residualC=TRUE, doubleMC=FALSE)

# Double-mean centering / two-way interaction / match-paired
dat3 <- indProd(attitude[,-1], var1=1:3, var2=4:6, match=FALSE, meanC=TRUE, residualC=FALSE, doubleMC=TRUE)

# Mean centering / three-way interaction / match-paired
dat4 <- indProd(attitude[,-1], var1=1:2, var2=3:4, var3=5:6)

# Residual centering / three-way interaction / match-paired
dat5 <- indProd(attitude[,-1], var1=1:2, var2=3:4, var3=5:6, match=FALSE, meanC=FALSE, residualC=TRUE, doubleMC=FALSE)

# Double-mean centering / three-way interaction / match-paired
dat6 <- indProd(attitude[,-1], var1=1:2, var2=3:4, var3=5:6, match=FALSE, meanC=TRUE, residualC=TRUE, doubleMC=TRUE)
```

---

kurtosis

*Finding excessive kurtosis*

---

### Description

Finding excessive kurtosis (g2) of an object

### Usage

```
kurtosis(object, population=FALSE)
```

### Arguments

object	A vector used to find a excessive kurtosis
population	TRUE to compute the parameter formula. FALSE to compute the sample statistic formula.



## Details

The excessive kurtosis computed is  $g_2$ . The parameter excessive kurtosis  $\gamma_2$  formula is

$$\gamma_2 = \frac{\mu_4}{\mu_2^2} - 3,$$

where  $\mu_i$  denotes the  $i$  order central moment.

The excessive kurtosis formula for sample statistic  $g_2$  is

$$g_2 = \frac{k_4}{k_2^2},$$

where  $k_i$  are the  $i$  order  $k$ -statistic.

The standard error of the excessive kurtosis is

$$Var(\hat{g}_2) = \frac{24}{N}$$

where  $N$  is the sample size.

## Value

A value of an excessive kurtosis with a test statistic if the population is specified as FALSE

## Author(s)

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

## References

Weisstein, Eric W. (n.d.). *Kurtosis*. Retrived from MathWorld—A Wolfram Web Resource <http://mathworld.wolfram.com/Kurtosis.html>

## See Also

- [skew](#) Find the univariate skewness of a variable
- [mardiaSkew](#) Find the Mardia's multivariate skewness of a set of variables
- [mardiaKurtosis](#) Find the Mardia's multivariate kurtosis of a set of variables

## Examples

```
kurtosis(1:5)
```

longInvariance

*Measurement Invariance Tests Within Person***Description**

Testing measurement invariance across timepoints (longitudinal) or any context involving the use of the same scale in one case (e.g., a dyad case with husband and wife answering the same scale). The measurement invariance uses a typical sequence of model comparison tests. This function currently works with only one scale.

**Usage**

```
longInvariance(model, varList, auto = "all", constrainAuto = FALSE,
  fixed.x = TRUE, std.lv = FALSE, group=NULL, group.equal="",
  group.partial="", warn=TRUE, debug=FALSE, strict = FALSE, quiet = FALSE,
  ...)
```

**Arguments**

model	lavaan syntax or parameter table
varList	A list containing indicator names of factors used in the invariance testing, such as the list that the first element is the vector of indicator names in the first timepoint and the second element is the vector of indicator names in the second timepoint. The order of indicator names should be the same (but measured in different times or different units).
auto	The order of autocorrelation on the measurement errors on the similar items across factor (e.g., Item 1 in Time 1 and Time 2). If 0 is specified, the autocorrelation will be not imposed. If 1 is specified, the autocorrelation will imposed for the adjacent factor listed in varList. The maximum number can be specified is the number of factors specified minus 1. If "all" is specified, the maximum number of order will be used.
constrainAuto	If TRUE, the function will equate the auto-covariance to be equal within the same item across factors. For example, the covariance of item 1 in time 1 and time 2 is equal to the covariance of item 1 in time 2 and time 3.
fixed.x	See <a href="#">lavaan</a> .
std.lv	See <a href="#">lavaan</a> .
group	See <a href="#">lavaan</a> .
group.equal	See <a href="#">lavaan</a> .
group.partial	See <a href="#">lavaan</a> .
warn	See <a href="#">lavaan</a> .
debug	See <a href="#">lavaan</a> .
strict	If TRUE, the sequence requires 'strict' invariance. See details for more information.
quiet	If TRUE, a summary is printed out containing an overview of the different models that are fitted, together with some model comparison tests.
...	Additional arguments in the <a href="#">lavaan</a> function.

## Details

If `strict = FALSE`, the following four models are tested in order:

1. Model 1: configural invariance. The same factor structure is imposed on all units.
2. Model 2: weak invariance. The factor loadings are constrained to be equal across units.
3. Model 3: strong invariance. The factor loadings and intercepts are constrained to be equal across units.
4. Model 4: The factor loadings, intercepts and means are constrained to be equal across units.

Each time a more restricted model is fitted, a chi-square difference test is reported, comparing the current model with the previous one, and comparing the current model to the baseline model (Model 1). In addition, the difference in cfi is also reported (delta.cfi).

If `strict = TRUE`, the following five models are tested in order:

1. Model 1: configural invariance. The same factor structure is imposed on all units.
2. Model 2: weak invariance. The factor loadings are constrained to be equal across units.
3. Model 3: strong invariance. The factor loadings and intercepts are constrained to be equal across units.
4. Model 4: strict invariance. The factor loadings, intercepts and residual variances are constrained to be equal across units.
5. Model 5: The factor loadings, intercepts, residual variances and means are constrained to be equal across units.

Note that if the chi-square test statistic is scaled (eg. a Satorra-Bentler or Yuan-Bentler test statistic), a special version of the chi-square difference test is used as described in <http://www.statmodel.com/chidiff.shtml>

## Value

Invisibly, all model fits in the sequence are returned as a list.

## Author(s)

Sunthud Pornprasertmanit (University of Kansas; <[psunthud@ku.edu](mailto:psunthud@ku.edu)>); Yves Rosseel (Ghent University; <[Yves.Rosseel@UGent.be](mailto:Yves.Rosseel@UGent.be)>)

## References

Vandenberg, R. J., and Lance, C. E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods*, 3, 4-70.

## See Also

[measurementinvariance](#) For the measurement invariance test between groups

**Examples**

```

model <- ' f1t1 =~ y1t1 + y2t1 + y3t1
           f1t2 =~ y1t2 + y2t2 + y3t2
           f1t3 =~ y1t3 + y2t3 + y3t3'

# Create list of variables
var1 <- c("y1t1", "y2t1", "y3t1")
var2 <- c("y1t2", "y2t2", "y3t2")
var3 <- c("y1t3", "y2t3", "y3t3")
constrainedVar <- list(var1, var2, var3)

# Invariance of the same factor across timepoints
longInvariance(model, auto=1, constrainAuto=TRUE, varList=constrainedVar, data=exLong)

# Invariance of the same factor across timepoints and groups
longInvariance(model, auto=1, constrainAuto=TRUE, varList=constrainedVar, data=exLong, group="sex", group.

```

mardiaKurtosis

*Finding Mardia's multivariate kurtosis***Description**

Finding Mardia's multivariate kurtosis of multiple variables

**Usage**

```
mardiaKurtosis(dat)
```

**Arguments**

`dat` The target matrix or data frame with multiple variables

**Details**

The Mardia's multivariate kurtosis formula (Mardia, 1970) is

$$b_{2,d} = \frac{1}{n} \sum_{i=1}^n \left[ (\mathbf{X}_i - \bar{\mathbf{X}})' \mathbf{S}^{-1} (\mathbf{X}_i - \bar{\mathbf{X}}) \right]^2,$$

where  $d$  is the number of variables,  $\mathbf{X}$  is the target dataset with multiple variables,  $n$  is the sample size,  $\mathbf{S}$  is the sample covariance matrix of the target dataset, and  $\bar{\mathbf{X}}$  is the mean vectors of the target dataset binded in  $n$  rows. When the population multivariate kurtosis is normal, the  $b_{2,d}$  is asymptotically distributed as normal distribution with the mean of  $d(d+2)$  and variance of  $8d(d+2)/n$ .

**Value**

A value of a Mardia's multivariate kurtosis with a test statistic

**Author(s)**

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

## References

Mardia, K. V. (1970). Measures of multivariate skewness and kurtosis with applications. *Biometrika*, 57, 519-530.

## See Also

- [skew](#) Find the univariate skewness of a variable
- [kurtosis](#) Find the univariate excessive kurtosis of a variable
- [mardiaSkew](#) Find the Mardia's multivariate skewness of a set of variables

## Examples

```
library(lavaan)
mardiaKurtosis(HolzingerSwineford1939[,paste("x", 1:9, sep="")])
```

---

mardiaSkew	<i>Finding Mardia's multivariate skewness</i>
------------	---

---

## Description

Finding Mardia's multivariate skewness of multiple variables

## Usage

```
mardiaSkew(dat)
```

## Arguments

**dat**                      The target matrix or data frame with multiple variables

## Details

The Mardia's multivariate skewness formula (Mardia, 1970) is

$$b_{1,d} = \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n \left[ (\mathbf{X}_i - \bar{\mathbf{X}})' \mathbf{S}^{-1} (\mathbf{X}_j - \bar{\mathbf{X}}) \right]^3,$$

where  $d$  is the number of variables,  $X$  is the target dataset with multiple variables,  $n$  is the sample size,  $S$  is the sample covariance matrix of the target dataset, and  $\bar{X}$  is the mean vectors of the target dataset binded in  $n$  rows. When the population multivariate skewness is normal, the  $\frac{n}{6} b_{1,d}$  is asymptotically distributed as chi-square distribution with  $d(d+1)(d+2)/6$  degrees of freedom.

## Value

A value of a Mardia's multivariate skewness with a test statistic

## Author(s)

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

## References

Mardia, K. V. (1970). Measures of multivariate skewness and kurtosis with applications. *Biometrika*, 57, 519-530.

## See Also

- [skew](#) Find the univariate skewness of a variable
- [kurtosis](#) Find the univariate excessive kurtosis of a variable
- [mardiaKurtosis](#) Find the Mardia's multivariate kurtosis of a set of variables

## Examples

```
library(lavaan)
mardiaSkew(HolzingerSwineford1939[,paste("x", 1:9, sep="")])
```

---

measurementInvariance *Measurement Invariance Tests*

---

## Description

Testing measurement invariance across groups using a typical sequence of model comparison tests.

## Usage

```
measurementInvariance(..., strict = FALSE, quiet = FALSE)
```

## Arguments

...	The same arguments as for any lavaan model. See <a href="#">cfa</a> for more information.
strict	If TRUE, the sequence requires 'strict' invariance. See details for more information.
quiet	If TRUE, a summary is printed out containing an overview of the different models that are fitted, together with some model comparison tests.

## Details

If `strict = FALSE`, the following four models are tested in order:

1. Model 1: configural invariance. The same factor structure is imposed on all groups.
2. Model 2: weak invariance. The factor loadings are constrained to be equal across groups.
3. Model 3: strong invariance. The factor loadings and intercepts are constrained to be equal across groups.
4. Model 4: The factor loadings, intercepts and means are constrained to be equal across groups.

Each time a more restricted model is fitted, a chi-square difference test is reported, comparing the current model with the previous one, and comparing the current model to the baseline model (Model 1). In addition, the difference in cfi is also reported (delta.cfi).

If `strict = TRUE`, the following five models are tested in order:

1. Model 1: configural invariance. The same factor structure is imposed on all groups.

2. Model 2: weak invariance. The factor loadings are constrained to be equal across groups.
3. Model 3: strong invariance. The factor loadings and intercepts are constrained to be equal across groups.
4. Model 4: strict invariance. The factor loadings, intercepts and residual variances are constrained to be equal across groups.
5. Model 5: The factor loadings, intercepts, residual variances and means are constrained to be equal across groups.

Note that if the chi-square test statistic is scaled (eg. a Satorra-Bentler or Yuan-Bentler test statistic), a special version of the chi-square difference test is used as described in <http://www.statmodel.com/chidiff.shtml>

### Value

Invisibly, all model fits in the sequence are returned as a list.

### Author(s)

Yves Rosseel <Yves.Rosseel@UGent.be>

### References

Vandenberg, R. J., and Lance, C. E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods*, 3, 4-70.

### See Also

[longInvariance](#) For the measurement invariance test within person

### Examples

```
HW.model <- ' visual =~ x1 + x2 + x3
              textual =~ x4 + x5 + x6
              speed =~ x7 + x8 + x9 '

measurementInvariance(HW.model, data=HolzingerSwineford1939, group="school")
```

---

miPoolChi

---

*Function to pool chi-square statistics from the result from multiple imputation*


---

### Description

The function combines likelihood ratio chi-square statistics from an analysis of multiply imputed data sets using the method proposed by Li, Meng, Raghunathan, and Rubin (1991, p. 74).

### Usage

```
miPoolChi(chis, df)
```

**Arguments**

chis	A vector of chi-square statistics
df	Degree of freedom that the chi-square statistics are based on

**Details**

The chi-square statistics are pooled by the procedure proposed by Li, Meng, Raghunathan, and Rubin (1991; Equations 2.1, 2.2, 2.16, and 2.17).

**Value**

The resulting value from the pooled chi-square is F-statistic. If the denominator degree of freedom is large, the F value multiplied by the numerator degree of freedom will approximate the chi-square statistics.

**Author(s)**

Craig Enders originally wrote this function in SAS, <http://psychology.clas.asu.edu/files/CombiningLikelihoodRatioChi-SquareStatisticsFromMIAnalysis.sas>. Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>) modified the function to run in R.

**References**

Li, K. H., Meng, X. L., Raghunathan, T. E., & Rubin, D. B. (1991). Significance levels from repeated p-values with multiply-imputed data. *Statistica Sinica*, 1, 65-92.

**Examples**

```
miPoolChi(c(89.864, 81.116, 71.500, 49.022, 61.986, 64.422, 55.256, 57.890, 79.416, 63.944), 2)
```

---

miPowerFit	<i>Modification indices and their power approach for model fit evaluation</i>
------------	---

---

**Description**

The model fit evaluation approach using modification indices and their power proposed by Saris, Satorra, and van der Veld (2009, pp. 570-573).

**Usage**

```
miPowerFit(lavaanObj, stdLoad=0.4, cor=0.1, stdBeta=0.1, intcept=0.2, stdDelta=NULL, delta=NULL)
```

**Arguments**

lavaanObj	The lavaan model object used to evaluate model fit
stdLoad	The amount of standardized factor loading that one would like to be detected (rejected). The default value is 0.4, which is suggested by Saris and colleagues (2009, p. 571).
cor	The amount of factor or error correlations that one would like to be detected (rejected). The default value is 0.1, which is suggested by Saris and colleagues (2009, p. 571).



stdBeta	The amount of standardized regression coefficients that one would like to be detected (rejected). The default value is 0.1, which is suggested by Saris and colleagues (2009, p. 571).
intcept	The amount of standardized intercept (similar to Cohen's $d$ that one would like to be detected (rejected). The default value is 0.2, which is equivalent to a low effect size proposed by Cohen (1988, 1992).
stdDelta	The vector of the standardized parameters that one would like to be detected (rejected). If this argument is specified, the value here will overwrite the other arguments above. The order of the vector must be the same as the row order from modification indices from the lavaan object. If a single value is specified, the value will be applied to all parameters.
delta	The vector of the unstandardized parameters that one would like to be detected (rejected). If this argument is specified, the value here will overwrite the other arguments above. The order of the vector must be the same as the row order from modification indices from the lavaan object. If a single value is specified, the value will be applied to all parameters.

## Details

In the lavaan object, one can inspect the modification indices and expected parameter changes. Those values can be used to evaluate model fit by the method proposed by Saris and colleagues (2009). First, one should evaluate whether the modification index of each parameter is significant. Second, one should evaluate whether the power to detect a target expected parameter change is high enough. If the modification index is not significant and the power is high, there is no misspecification. If the modification index is significant and the power is low, the fixed parameter is misspecified. If the modification index is significant and the power is high, the expected parameter change is investigated. If the expected parameter change is large (greater than the target expected parameter change), the parameter is misspecified. If the expected parameter change is low (lower than the target expected parameter change), the parameter is not misspecified. If the modification index is not significant and the power is low, the decision is inconclusive.

## Value

A data frame with these variables:

1. lhs The left-hand side variable (with respect to the lavaan operator)
2. op The lavaan syntax operator: "~~" represents covariance, "=~" represents factor loading, "~" represents regression, and "~1" represents intercept.
3. rhs The right-hand side variable (with respect to the lavaan operator)
4. group The group of the parameter
5. mi The modification index of the fixed parameter
6. epc The expected parameter change if the parameter is freely estimated
7. target.epc The target expected parameter change that represents the minimum size of misspecification that one would like to be detected by the test with a high power
8. std.epc The standardized expected parameter change if the parameter is freely estimated
9. std.target.epc The standardized target expected parameter change
10. significant.mi Represents whether the modification index value is significant
11. high.power Represents whether the power is enough to detect the target expected parameter change

12. decision The decision whether the parameter is misspecified or not: "M" represents the parameter is misspecified, "NM" represents the parameter is not misspecified, "EPC:M" represents the parameter is misspecified decided by checking the expected parameter change value, "EPC:NM" represents the parameter is not misspecified decided by checking the expected parameter change value, and "I" represents the decision is inconclusive.

### Author(s)

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

### References

- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Erlbaum.
- Cohen, J. (1992). A power primer. *Psychological Bulletin*, 112, 155-159.
- Saris, W. E., Satorra, A., & van der Veld, W. M. (2009). Testing structural equation models or detection of misspecifications? *Structural Equation Modeling*, 16, 561-582.

### See Also

[moreFitIndices](#) For the additional fit indices information

### Examples

```
library(lavaan)

HS.model <- ' visual =~ x1 + x2 + x3
              textual =~ x4 + x5 + x6
              speed =~ x7 + x8 + x9 '

fit <- cfa(HS.model, data=HolzingerSwineford1939, group="sex", meanstructure=TRUE)
miPowerFit(fit)

model <- '
# latent variable definitions
ind60 =~ x1 + x2 + x3
dem60 =~ y1 + a*y2 + b*y3 + c*y4
dem65 =~ y5 + a*y6 + b*y7 + c*y8

# regressions
dem60 ~ ind60
dem65 ~ ind60 + dem60

# residual correlations
y1 ~~ y5
y2 ~~ y4 + y6
y3 ~~ y7
y4 ~~ y8
y6 ~~ y8
,

fit2 <- sem(model, data=PoliticalDemocracy, meanstructure=TRUE)
miPowerFit(fit2, stdLoad=0.3, cor=0.2, stdBeta=0.2, intcept=0.5)
```

**Description**

This function takes an expression for an indirect effect, the parameters and standard errors associated with the expression and returns a confidence interval based on a Monte Carlo test of mediation (MacKinnon, Lockwood, & Williams, 2004).

**Usage**

```
monteCarloMed(expression, ..., ACM=NULL, rep=20000, CI=95, plot=FALSE, outputValues=FALSE)
```

**Arguments**

expression	A character scalar representing the computation of an indirect effect. Different parameters in the expression should have different alphanumeric values. Expressions can use either addition (+) or multiplication (*) operators.
...	Parameter estimates for all parameters named in expression. The order of parameters should follow from expression (the first parameter named in expression should be the first parameter listed in ...). Alternatively ...can be a vector of parameter estimates.
ACM	A matrix representing the asymptotic covariance matrix of the parameters described in expression. This matrix should be a symmetric matrix with dimensions equal to the number of parameters names in expression. Information on finding the ACOV is popular SEM software is described below.)
rep	The number of replications to compute. Many thousand are recommended.
CI	Width of the confidence interval computed.
plot	Should the function output a plot of simulated values of the indirect effect?
outputValues	Should the function output all simulated values of the indirect effect?

**Details**

This function implements the Monte Carlo test of mediation first described in MacKinnon, Lockwood, & Williams (2004) and extends it to complex cases where the indirect effect is more than a function of two parameters. The function takes an expression for the indirect effect, randomly simulated values of the indirect effect based on the values of the parameters (and the associated standard errors) comprising the indirect effect, and outputs a confidence interval of the indirect effect based on the simulated values. For further information on the Monte Carlo test of mediation see MacKinnon, Lockwood, & Williams (2004), Preacher & Selig (in press), and Selig & Preacher (2008). For a Monte Carlo test of mediation with a random effects model see Selig & Preacher (2010).

The asymptotic covariance matrix can be easily found in many popular SEM software applications.

- LISREL Including the EC option on the OU line will print the ACM to a separate file. The file contains the lower triangular elements of the ACM in free format and scientific notation
- Mplus Include the command TECH3; in the OUTPUT section. The ACM will be printed in the output.
- lavaan Use the command vcov on the fitted lavaan object to print the ACM to the screen

## Value

A matrix with values for the upper and lower limits of the confidence interval generated from the Monte Carlo test of mediation. If `outputValues=TRUE`, output will be a list with a matrix with values for the upper and lower limits of the confidence interval as the first element and a vector of simulated values of the indirect effect as the second element.

## Author(s)

Corbin Quick (University of Kansas; <corbing@ku.edu>) Alexander M. Schoemann (University of Kansas; <schoemann@ku.edu>) James P. Selig (University of New Mexico; <selig@unm.edu>)

## References

Preacher, K. J., & Selig, J. P. (2010, July). Monte Carlo method for assessing multilevel mediation: An interactive tool for creating confidence intervals for indirect effects in 1-1-1 multilevel models [Computer software]. Available from <http://quantpsy.org/>.

Preacher, K. J., & Selig, J. P. (in press). Advantages of Monte Carlo confidence intervals for indirect effects. *Communication Methods and Measures*.

Selig, J. P., & Preacher, K. J. (2008, June). Monte Carlo method for assessing mediation: An interactive tool for creating confidence intervals for indirect effects [Computer software]. Available from <http://quantpsy.org/>.

## Examples

```
#Simple two path mediation
#Write expression of indirect effect
med <- 'a*b'
#Parameter values from analyses
aparam <- 1
bparam<-2
#Asymptotic covariance matrix from analyses
AC <- matrix(c(.01,.00002,
               .00002,.02), nrow=2, byrow=TRUE)
#Compute CI, include a plot
monteCarloMed(med, coef1=aparam, coef2=bparam, outputValues=FALSE, plot=TRUE, ACM=AC)

#Use a matrix of parameter estimates as input
aparam<-c(1,2)
monteCarloMed(med, coef1=aparam, outputValues=FALSE, plot=TRUE, ACM=AC)
```

```
#complex mediation with two paths for the indirect effect
#Write expression of indirect effect
med <- 'a1*b1 + a1*b2'
#Parameter values and standard errors from analyses
aparam <- 1
b1param<-2
b2param<-1
#Asymptotic covariance matrix from analyses
AC <- matrix(c(1,.00002, .00003,
               .00002,1, .00002,
               .00003, .00002, 1), nrow=3, byrow=TRUE)
#Compute CI do not include a plot
monteCarloMed(med, coef1=aparam, coef2=b1param, coef3=b2param, ACM=AC)
```

---

moreFitIndices	<i>Calculate more fit indices</i>
----------------	-----------------------------------

---

### Description

Calculate more fit indices that are not already provided in lavaan.

### Usage

```
moreFitIndices(object, nPrior = 1)
```

### Arguments

object	The lavaan model object provided after running the cfa or the sem functions.
nPrior	The sample size on which prior is based. This argument is used to compute BIC*.

### Details

Normed Fit Index (nfi; West, Taylor, & Wu, 2012) is one of the relative fit indices which can be computed by

$$nfi = \frac{\chi_0^2 - \chi_k^2}{\chi_0^2},$$

where  $\chi_k^2$  is the chi-square test statistic value of the target model,  $\chi_0^2$  is the chi-square test statistic value of the null model.

Incremental Fit Index (ifi; West, Taylor, & Wu, 2012) is one of the relative fit indices which can be computed by

$$ifi = \frac{\chi_0^2 - \chi_k^2}{\chi_0^2 - df_k},$$

where  $df_k$  is the degree of freedom when fitting the target model

Gamma Hat (gfi\*; West, Taylor, & Wu, 2012) is one of the relative fit indices which can be computed by

$$gfi^* = \frac{p}{p + 2 \times \frac{\chi_k^2 - df_k}{N-1}},$$

where  $N$  is the sample size,  $p$  is the number of variables in the model. This formula assumes equal number of indicators across groups.

Adjusted Gamma Hat (agfi\*; West, Taylor, & Wu, 2012) is one of the relative fit indices which can be computed by

$$agfi^* = \left(1 - \frac{K \times p \times (p+1)}{2 \times df_k}\right) \times (1 - gfi^*),$$

where  $K$  is the number of group (please refer to Dudgeon, 2004 for the multiple-group adjustment for agfi\*).

Corrected Akaike Information Criterion (AICc; Burnham & Anderson, 2003) is the corrected version of aic for small sample size:

$$aicc = f + \frac{2k(k+1)}{N-k-1},$$

where  $f$  is the minimized discrepancy function, which is the product of the log likelihood and -2, and  $k$  is the number of parameters in the target model.

Expected Value of Cross-Validation Index (ECVI; West, Taylor, & Wu, 2012) is the average discrepancy in the fitted covariance matrices between two samples of equal sample size across all possible combinations of two samples from the same population:

$$ecvi = f + \frac{2 \times k}{N},$$

Stochastic information criterion (sic; Preacher, 2006) is similar to aic or bic. This index will account for model complexity in the model's function form, in addition to the number of free parameters. sic can be computed by

$$sic = \frac{1}{2} \left( f - \log \det I(\hat{\theta}) \right),$$

where  $I(\hat{\theta})$  is the information matrix of the parameters.

Corrected Bayesian Information Criterion (BIC\*; Kuha, 2004) is similar to bic but explicitly specifying the sample size on which the prior is based ( $N_{prior}$ ).

$$bicc = f + k \log (1 + N/N_{prior}),$$

Hannan-Quinn Information Criterion (hqc; Hannan & Quinn, 1979) is used for model selection similar to aic or bic.

$$hqc = f + 2k \log (\log N),$$

## Value

1. nfi Normed Fit Index
2. ifi Incremental Fit Index
3. gfi\* Gamma Hat
4. agfi\* Adjusted Gamma Hat
5. aicc Corrected Akaike Information Criterion
6. ecvi Expected Value of Cross-Validation Index
7. sic Stochastic Information Criterion
8. bic\* Bayesian Information Criterion with specifying the prior sample size
9. hqc Hannan-Quinn Information Criterion

## Author(s)

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>) Aaron Boulton (University of Kansas; <aboulton@ku.edu>)

## References

- Burnham, K., & Anderson, D. (2003). *Model selection and multimodel inference: A practical-theoretic approach*. New York, NY: Springer-Verlag.
- Dudgeon, P. (2004). A note on extending Steiger's (1998) multiple sample RMSEA adjustment to other noncentrality parameter-based statistic. *Structural Equation Modeling*, 11, 305-319.
- Kuha, J. (2004). AIC and BIC: Comparisons of assumptions and performance. *Sociological Methods Research*, 33, 188-229.
- Preacher, K. J. (2006). Quantifying parsimony in structural equation modeling. *Multivariate Behavioral Research*, 43, 227-259.
- West, S. G., Taylor, A. B., & Wu, W. (2012). Model fit and model selection in structural equation modeling. In R. H. Hoyle (Ed.), *Handbook of Structural Equation Modeling*. New York: Guilford.

## See Also

[miPowerFit](#) For the modification indices and their power approach for model fit evaluation

## Examples

```
HS.model <- ' visual =~ x1 + x2 + x3
              textual =~ x4 + x5 + x6
              speed  =~ x7 + x8 + x9 '

fit <- cfa(HS.model, data=HolzingerSwineford1939)
moreFitIndices(fit)
```

---

parcelAllocation	<i>Random Allocation of Items to Parcels in a Structural Equation Model</i>
------------------	---

---

## Description

This function generates a given number of randomly generated item-to-parcel allocations, fits a model to each allocation, and provides averaged results over all allocations.

## Usage

```
parcelAllocation(nPerPar, facPlc, nAlloc=100, syntax, dataset, names='default', leaveout=0, ...)
```

## Arguments

- |         |  |
|---------|--|
| nPerPar | A list in which each element is a vector corresponding to each factor indicating sizes of parcels. If variables are left out of parceling, they should not be accounted for here (there should NOT be parcels of size "1").                          |
| facPlc  | A list of vectors, each corresponding to a factor, specifying the variables in that factor (whether included in parceling or not). Either variable names or column numbers. Variables not listed will not be modeled or included in output datasets. |
| nAlloc  | The number of random allocations of items to parcels to generate.  |
| syntax  | <a href="#">lavaan</a> syntax. If substituted with a file name, parcelAllocation will print output data sets to a specified folder rather than analyzing using lavaan (note for Windows users: file path must be specified using forward slashes).   |

dataset	Data set. Can be file path or R object (matrix or dataframe). If the data has missing values multiple imputation before parceling is recommended.
names	(Optional) A character vector containing the names of parceled variables.
leaveout	A vector of variables to be left out of randomized parceling. Either variable names or column numbers are allowed.
...	Additional arguments to be passed to <a href="#">lavaan</a>

## Details

This function implements the random item to parcel allocation procedure described in Sterba (2011) and Sterba and MccCallum (2010). The function takes a single data set with item level data, randomly assigns items to parcels, fits a structural equation model to the parceled data (using [lavaan](#)), and repeats this process for a user specified number of random allocations. Results from all fitted models are summarized and output. For further details on the benefits of the random allocation of items to parcels see Sterba (2011) and Sterba and MccCallum (2010).

## Value

Estimates	A data frame containing results related to parameter estimates with columns corresponding to parameter names, average parameter estimates across allocations, the standard deviation of parameter estimates across allocations, the minimum parameter estimate across allocations, the maximum parameter estimate across allocations, the range of parameter estimates across allocations, and the proportions of allocations in which the parameter estimate is significant.
SE	A data frame containing results related to standard errors with columns corresponding to parameter names, average standard errors across allocations, the standard deviation of standard errors across allocations, the minimum standard error across allocations, the maximum standard error across allocations, and the range of standard errors across allocations.
Fit	A data frame containing results related to model fit with columns corresponding to fit index names, the average of each index across allocations, the standard deviation of each fit index across allocations, the minimum of each fit index across allocations, the maximum of each fit index across allocations, and the range of each fit index across allocations.

## Author(s)

Corbin Quick (University of Kansas; <corbinq@ku.edu>) Alexander M. Schoemann (University of Kansas; <schoemann@ku.edu>)

## References

- Sterba, S.K. (2011). Implications of parcel-allocation variability for comparing fit of item-solutions and parcel-solutions. *Structural Equation Modeling*, 18, 554-577.
- Sterba, S.K. & MacCallum, R.C. (2010). Variability in parameter estimates and model fit across random allocations of items to parcels. *Multivariate Behavioral Research*, 45, 322-358.

## Examples

```
#Fit 3 factor CFA to simulated data.
#Each factor has 9 indicators that are randomly parceled into 3 parcels
#Lavaan syntax for the model to be fit to parceled data
```



```

syntax <- 'La =~ V1 + V2 + V3
          Lb =~ V4 + V5 + V6
,
#Parcel and fit data 20 times. The actual parcel number should be higher than 20 times.
name1 <- colnames(simParcel)[1:9]
name2 <- colnames(simParcel)[10:18]
parcelAllocation(list(c(3,3,3),c(3,3,3)), list(name1, name2), nAlloc=20, syntax=syntax, dataset=simParcel)

```

plotProbe

*Plot the graphs for probing latent interaction*

## Description

This function will plot the line graphs representing the simple effect of the independent variable given the values of the moderator.

## Usage

```
plotProbe(object, xlim, xlab="Independent Variable", ylab="Dependent Variable", ...)
```

## Arguments

object	The result of probing latent interaction obtained from <a href="#">probe2WayMC</a> , <a href="#">probe2WayRC</a> , <a href="#">probe3WayMC</a> , or <a href="#">probe3WayRC</a> function.
xlim	The vector of two numbers: the minimum and maximum values of the independent variable
xlab	The label of the x-axis
ylab	The label of the y-axis
...	Any addition argument for the <a href="#">plot</a> function

## Value

None. This function will plot the simple main effect only.

## Author(s)

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

## See Also

- [indProd](#) For creating the indicator products with no centering, mean centering, double-mean centering, or residual centering.
- [probe2WayMC](#) For probing the two-way latent interaction when the results are obtained from mean-centering, or double-mean centering.
- [probe3WayMC](#) For probing the three-way latent interaction when the results are obtained from mean-centering, or double-mean centering.
- [probe2WayRC](#) For probing the two-way latent interaction when the results are obtained from residual-centering approach.
- [probe3WayRC](#) For probing the two-way latent interaction when the results are obtained from residual-centering approach.

**Examples**

```

library(lavaan)

dat2wayMC <- indProd(dat2way, 1:3, 4:6)

model1 <- "
f1 =~ x1 + x2 + x3
f2 =~ x4 + x5 + x6
f12 =~ x1.x4 + x2.x5 + x3.x6
f3 =~ x7 + x8 + x9
f3 ~ f1 + f2 + f12
f12 ~~ 0*f1
f12 ~~ 0*f2
x1 ~ 0*1
x4 ~ 0*1
x1.x4 ~ 0*1
x7 ~ 0*1
f1 ~ NA*1
f2 ~ NA*1
f12 ~ NA*1
f3 ~ NA*1
"

fitMC2way <- sem(model1, data=dat2wayMC, meanstructure=TRUE, std.lv=FALSE)
result2wayMC <- probe2WayMC(fitMC2way, c("f1", "f2", "f12"), "f3", "f2", c(-1, 0, 1))
plotProbe(result2wayMC, xlim=c(-2, 2))

dat3wayMC <- indProd(dat3way, 1:3, 4:6, 7:9)

model3 <- "
f1 =~ x1 + x2 + x3
f2 =~ x4 + x5 + x6
f3 =~ x7 + x8 + x9
f12 =~ x1.x4 + x2.x5 + x3.x6
f13 =~ x1.x7 + x2.x8 + x3.x9
f23 =~ x4.x7 + x5.x8 + x6.x9
f123 =~ x1.x4.x7 + x2.x5.x8 + x3.x6.x9
f4 =~ x10 + x11 + x12
f4 ~ f1 + f2 + f3 + f12 + f13 + f23 + f123
f1 ~~ 0*f12
f1 ~~ 0*f13
f1 ~~ 0*f123
f2 ~~ 0*f12
f2 ~~ 0*f23
f2 ~~ 0*f123
f3 ~~ 0*f13
f3 ~~ 0*f23
f3 ~~ 0*f123
f12 ~~ 0*f123
f13 ~~ 0*f123
f23 ~~ 0*f123
x1 ~ 0*1
x4 ~ 0*1
x7 ~ 0*1
x10 ~ 0*1

```

```

x1.x4 ~ 0*1
x1.x7 ~ 0*1
x4.x7 ~ 0*1
x1.x4.x7 ~ 0*1
f1 ~ NA*1
f2 ~ NA*1
f3 ~ NA*1
f12 ~ NA*1
f13 ~ NA*1
f23 ~ NA*1
f123 ~ NA*1
f4 ~ NA*1
"

fitMC3way <- sem(model3, data=dat3wayMC, meanstructure=TRUE, std.lv=FALSE)
result3wayMC <- probe3WayMC(fitMC3way, c("f1", "f2", "f3", "f12", "f13", "f23", "f123"), "f4", c("f1", "f2", "f3", "f12", "f13", "f23", "f123"))
plotProbe(result3wayMC, xlim=c(-2, 2))

```

plotRMSEAdist

*Plot the sampling distributions of RMSEA***Description**

Plots the sampling distributions of RMSEA based on the noncentral chi-square distributions

**Usage**

```
plotRMSEAdist(rmsea, n, df, ptile=NULL, caption=NULL, rmseaScale = TRUE, group=1)
```

**Arguments**

rmsea	The vector of RMSEA values to be plotted
n	Sample size of a dataset
df	Model degrees of freedom
ptile	The percentile rank of the distribution of the first RMSEA that users wish to plot a vertical line in the resulting graph
caption	The name vector of each element of rmsea
rmseaScale	If TRUE, the RMSEA scale is used in the x-axis. If FALSE, the chi-square scale is used in the x-axis.
group	The number of group that is used to calculate RMSEA.

**Details**

This function creates overlapping plots of the sampling distribution of RMSEA based on non-central chi-square distribution (MacCallum, Browne, & Suguwara, 1996). First, the noncentrality parameter ( $\lambda$ ) is calculated from RMSEA (Steiger, 1998; Dudgeon, 2004) by

$$\lambda = (N - 1)d\varepsilon^2/K,$$

where  $N$  is sample size,  $d$  is the model degree of freedom,  $K$  is the number of group and  $\varepsilon$  is the population RMSEA. Next, the noncentral chi-square distribution with a specified degree of freedom

and noncentrality parameter is plotted. Thus, the x-axis represent the sample chi-square value. The sample chi-square value can be transformed to the sample RMSEA scale ( $\hat{\varepsilon}$ ) by

$$\hat{\varepsilon} = \sqrt{K} \sqrt{\frac{\chi^2 - d}{(N - 1)d}},$$

where  $\chi^2$  is the chi-square value obtained from the noncentral chi-square distribution.

### Author(s)

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

### References

- Dudgeon, P. (2004). A note on extending Steiger's (1998) multiple sample RMSEA adjustment to other noncentrality parameter-based statistic. *Structural Equation Modeling*, 11, 305-319.
- MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, 1, 130-149.
- Steiger, J. H. (1998). A note on multiple sample extensions of the RMSEA fit index. *Structural Equation Modeling*, 5, 411-419.

### See Also

- [plotRMSEApower](#) to plot the statistical power based on population RMSEA given the sample size
- [findRMSEApower](#) to find the statistical power based on population RMSEA given a sample size
- [findRMSEAsamplesize](#) to find the minium sample size for a given statistical power based on population RMSEA

### Examples

```
plotRMSEAdist(rmse=c(.05, .08), n=200, df=20, ptile=0.95, rmseaScale = TRUE)
plotRMSEAdist(rmse=c(.05, .01), n=200, df=20, ptile=0.05, rmseaScale = FALSE)
```

---

plotRMSEApower

*Plot power curves for RMSEA*

---

### Description

Plots power of RMSEA over a range of sample sizes

### Usage

```
plotRMSEApower(rmse0, rmseaA, df, nlow, nhigh, steps=1, alpha=.05, group=1)
```

**Arguments**

rmsea0	Null RMSEA
rmseaA	Alternative RMSEA
df	Model degrees of freedom
nlow	Lower sample size
nhigh	Upper sample size
steps	Increase in sample size for each iteration. Smaller values of steps will lead to more precise plots. However, smaller step sizes means a longer run time.
alpha	Alpha level used in power calculations
group	The number of group that is used to calculate RMSEA.

**Details**

This function creates plot of power for RMSEA against a range of sample sizes. The plot places sample size on the horizontal axis and power on the vertical axis. The user should indicate the lower and upper values for sample size and the sample size between each estimate ("step size") We strongly urge the user to read the sources below (see References) before proceeding. A web version of this function is available at: <http://quantpsy.org/rmsea/rmseaplot.htm>.

**Value**

1. plot Plot of power for RMSEA against a range of sample sizes

**Author(s)**

Alexander M. Schoemann (University of Kansas; <schoemann@ku.edu>) Kristopher J. Preacher (Vanderbilt University; <kris.preacher@vanderbilt.edu>) Donna L. Coffman (Pennsylvania State University; <d1c30@psu.edu.>)

**References**

- MacCallum, R. C., Browne, M. W., & Cai, L. (2006). Testing differences between nested covariance structure models: Power analysis and null hypotheses. *Psychological Methods*, 11, 19-35.
- MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, 1, 130-149.
- MacCallum, R. C., Lee, T., & Browne, M. W. (2010). The issue of isopower in power analysis for tests of structural equation models. *Structural Equation Modeling*, 17, 23-41.
- Preacher, K. J., Cai, L., & MacCallum, R. C. (2007). Alternatives to traditional model comparison strategies for covariance structure models. In T. D. Little, J. A. Bovaird, & N. A. Card (Eds.), *Modeling contextual effects in longitudinal studies* (pp. 33-62). Mahwah, NJ: Lawrence Erlbaum Associates.
- Steiger, J. H. (1998). A note on multiple sample extensions of the RMSEA fit index. *Structural Equation Modeling*, 5, 411-419.
- Steiger, J. H., & Lind, J. C. (1980, June). *Statistically based tests for the number of factors*. Paper presented at the annual meeting of the Psychometric Society, Iowa City, IA.

See Also

- [plotRMSEAdist](#) to visualize the RMSEA distributions
- [findRMSEApower](#) to find the statistical power based on population RMSEA given a sample size
- [findRMSEAsamplesize](#) to find the minium sample size for a given statistical power based on population RMSEA

Examples

```
plotRMSEApower(.025, .075, 23, 100, 500, 10)
```

---

probe2WayMC	<i>Probing two-way interaction on the residual-centered latent interaction</i>
-------------	--

---

Description

Probing interaction for simple intercept and simple slope for the no-centered or mean-centered latent two-way interaction

Usage

```
probe2WayMC(fit, nameX, nameY, modVar, valProbe)
```

Arguments

fit	The lavaan model object used to evaluate model fit
nameX	The vector of the factor names used as the predictors. The first-order factor will be listed first. The last name must be the name representing the interaction term.
nameY	The name of factor that is used as the dependent variable.
modVar	The name of factor that is used as a moderator. The effect of the other independent factor on each moderator variable value will be probed.
valProbe	The values of the moderator that will be used to probe the effect of the other independent factor.

Details

Before using this function, researchers need to make the products of the indicators between the first-order factors using mean centering (Marsh, Wen, & Hau, 2004). Note that the double-mean centering may not be appropriate for probing interaction if researchers are interested in simple intercepts. The mean or double-mean centering can be done by the [indProd](#) function. The indicator products can be made for all possible combination or matched-pair approach (Marsh et al., 2004). Next, the hypothesized model with the regression with latent interaction will be used to fit all original indicators and the product terms. See the example for how to fit the product term below. Once the lavaan result is obtained, this function will be used to probe the interaction.

Let that the latent interaction model regressing the dependent variable ( $Y$ ) on the independent variable ( $X$ ) and the moderator ( $Z$ ) be

$$Y = b_0 + b_1X + b_2Z + b_3XZ + r,$$

where  $b_0$  is the estimated intercept or the expected value of  $Y$  when both  $X$  and  $Z$  are 0,  $b_1$  is the effect of  $X$  when  $Z$  is 0,  $b_2$  is the effect of  $Z$  when  $X$  is 0,  $b_3$  is the interaction effect between  $X$  and  $Z$ , and  $r$  is the residual term.

For probing two-way interaction, the simple intercept of the independent variable at each value of the moderator (Aiken & West, 1991; Cohen, Cohen, West, & Aiken, 2003; Preacher, Curran, & Bauer, 2006) can be obtained by

$$b_{0|X=0,Z} = b_0 + b_2Z.$$

The simple slope of the independent variable at each value of the moderator can be obtained by

$$b_{X|Z} = b_1 + b_3Z.$$

The variance of the simple intercept formula is

$$Var(b_{0|X=0,Z}) = Var(b_0) + 2ZCov(b_0, b_2) + Z^2Var(b_2)$$

where  $Var$  denotes the variance of a parameter estimate and  $Cov$  denotes the covariance of two parameter estimates.

The variance of the simple slope formula is

$$Var(b_{X|Z}) = Var(b_1) + 2ZCov(b_1, b_3) + Z^2Var(b_3)$$

Wald statistic is used for test statistic.

## Value

A list with two elements:

1. SimpleIntercept The intercepts given each value of the moderator. This element will be shown only if the factor intercept is estimated (e.g., not fixed as 0).
2. SimpleSlope The slopes given each value of the moderator.

In each element, the first column represents the values of the moderators specified in the valProbe argument. The second column is the simple intercept or simple slope. The third column is the standard error of the simple intercept or simple slope. The fourth column is the Wald ( $z$ ) statistic. The fifth column is the  $p$ -value testing whether the simple intercepts or slopes are different from 0.

## Author(s)

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

## References

- Aiken, L. S., & West, S. G. (1991). Multiple regression: Testing and interpreting interactions. Newbury Park, CA: Sage.
- Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). Applied multiple regression/correlation analysis for the behavioral sciences (3rd ed.). New York: Routledge.
- Marsh, H. W., Wen, Z., & Hau, K. T. (2004). Structural equation models of latent interactions: Evaluation of alternative estimation strategies and indicator construction. *Psychological Methods*, 9, 275-300.
- Preacher, K. J., Curran, P. J., & Bauer, D. J. (2006). Computational tools for probing interactions in multiple linear regression, multilevel modeling, and latent curve analysis. *Journal of Educational and Behavioral Statistics*, 31, 437-448.

**See Also**

- [indProd](#) For creating the indicator products with no centering, mean centering, double-mean centering, or residual centering.
- [probe3WayMC](#) For probing the three-way latent interaction when the results are obtained from mean-centering, or double-mean centering.
- [probe2WayRC](#) For probing the two-way latent interaction when the results are obtained from residual-centering approach.
- [probe3WayRC](#) For probing the two-way latent interaction when the results are obtained from residual-centering approach.
- [plotProbe](#) Plot the simple intercepts and slopes of the latent interaction.

**Examples**

```
library(lavaan)

dat2wayMC <- indProd(dat2way, 1:3, 4:6)

model1 <- "
f1 =~ x1 + x2 + x3
f2 =~ x4 + x5 + x6
f12 =~ x1.x4 + x2.x5 + x3.x6
f3 =~ x7 + x8 + x9
f3 ~ f1 + f2 + f12
f12 ~~0*f1
f12 ~~ 0*f2
x1 ~ 0*1
x4 ~ 0*1
x1.x4 ~ 0*1
x7 ~ 0*1
f1 ~ NA*1
f2 ~ NA*1
f12 ~ NA*1
f3 ~ NA*1
"

fitMC2way <- sem(model1, data=dat2wayMC, meanstructure=TRUE, std.lv=FALSE)
summary(fitMC2way)

result2wayMC <- probe2WayMC(fitMC2way, c("f1", "f2", "f12"), "f3", "f2", c(-1, 0, 1))
result2wayMC
```

probe2WayRC

*Probing two-way interaction on the residual-centered latent interaction***Description**

Probing interaction for simple intercept and simple slope for the residual-centered latent two-way interaction (Pornprasertmanit, Schoemann, Geldhof, & Little, submitted)

**Usage**

```
probe2WayRC(fit, nameX, nameY, modVar, valProbe)
```



## Arguments

fit	The lavaan model object used to evaluate model fit
nameX	The vector of the factor names used as the predictors. The first-order factor will be listed first. The last name must be the name representing the interaction term.
nameY	The name of factor that is used as the dependent variable.
modVar	The name of factor that is used as a moderator. The effect of the other independent factor on each moderator variable value will be probed.
valProbe	The values of the moderator that will be used to probe the effect of the other independent factor.

## Details

Before using this function, researchers need to make the products of the indicators between the first-order factors and residualize the products by the original indicators (Lance, 1988; Little, Bovaird, & Widaman, 2006). The process can be automated by the [indProd](#) function. Note that the indicator products can be made for all possible combination or matched-pair approach (Marsh et al., 2004). Next, the hypothesized model with the regression with latent interaction will be used to fit all original indicators and the product terms. See the example for how to fit the product term below. Once the lavaan result is obtained, this function will be used to probe the interaction.

The probing process on residual-centered latent interaction is based on transforming the residual-centered result into the no-centered result. See Pornprasertmanit, Schoemann, Geldhof, and Little (submitted) for further details. Note that this approach based on a strong assumption that the first-order latent variables are normally distributed. The probing process is applied after the no-centered result (parameter estimates and their covariance matrix among parameter estimates) has been computed. See the [probe2WayMC](#) for further details.

## Value

A list with two elements:

1. SimpleIntercept The intercepts given each value of the moderator. This element will be shown only if the factor intercept is estimated (e.g., not fixed as 0).
2. SimpleSlope The slopes given each value of the moderator.

In each element, the first column represents the values of the moderators specified in the valProbe argument. The second column is the simple intercept or simple slope. The third column is the standard error of the simple intercept or simple slope. The fourth column is the Wald ( $z$ ) statistic. The fifth column is the  $p$ -value testing whether the simple intercepts or slopes are different from 0.

## Author(s)

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

## References

- Lance, C. E. (1988). Residual centering, exploratory and confirmatory moderator analysis, and decomposition of effects in path models containing interactions. *Applied Psychological Measurement*, 12, 163-175.
- Little, T. D., Bovaird, J. A., & Widaman, K. F. (2006). On the merits of orthogonalizing powered and product terms: Implications for modeling interactions. *Structural Equation Modeling*, 13, 497-519.

Marsh, H. W., Wen, Z., & Hau, K. T. (2004). Structural equation models of latent interactions: Evaluation of alternative estimation strategies and indicator construction. *Psychological Methods*, 9, 275-300.

Pornprasertmanit, S., Schoemann, A. M., Geldhof, G. J., & Little, T. D. (submitted). *Probing latent interaction estimated with a residual centering approach.*

### See Also

- [indProd](#) For creating the indicator products with no centering, mean centering, double-mean centering, or residual centering.
- [probe2WayMC](#) For probing the two-way latent interaction when the results are obtained from mean-centering, or double-mean centering.
- [probe3WayMC](#) For probing the three-way latent interaction when the results are obtained from mean-centering, or double-mean centering.
- [probe3WayRC](#) For probing the two-way latent interaction when the results are obtained from residual-centering approach.
- [plotProbe](#) Plot the simple intercepts and slopes of the latent interaction.

### Examples

```
library(lavaan)

dat2wayRC <- orthogonalize(dat2way, 1:3, 4:6)

model1 <- "
f1 =~ x1 + x2 + x3
f2 =~ x4 + x5 + x6
f12 =~ x1.x4 + x2.x5 + x3.x6
f3 =~ x7 + x8 + x9
f3 ~ f1 + f2 + f12
f12 ~~ 0*f1
f12 ~~ 0*f2
x1 ~ 0*1
x4 ~ 0*1
x1.x4 ~ 0*1
x7 ~ 0*1
f1 ~ NA*1
f2 ~ NA*1
f12 ~ NA*1
f3 ~ NA*1
"

fitRC2way <- sem(model1, data=dat2wayRC, meanstructure=TRUE, std.lv=FALSE)
summary(fitRC2way)

result2wayRC <- probe2WayRC(fitRC2way, c("f1", "f2", "f12"), "f3", "f2", c(-1, 0, 1))
result2wayRC
```

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probe3WayMC	<i>Probing two-way interaction on the residual-centered latent interaction</i>
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### Description

Probing interaction for simple intercept and simple slope for the no-centered or mean-centered latent two-way interaction

### Usage

```
probe3WayMC(fit, nameX, nameY, modVar, valProbe1, valProbe2)
```

### Arguments

fit	The lavaan model object used to evaluate model fit
nameX	The vector of the factor names used as the predictors. The three first-order factors will be listed first. Then the second-order factors will be listed. The last element of the name will represent the three-way interaction. Note that the fourth element must be the interaction between the first and the second variables. The fifth element must be the interaction between the first and the third variables. The sixth element must be the interaction between the second and the third variables.
nameY	The name of factor that is used as the dependent variable.
modVar	The name of two factors that are used as the moderators. The effect of the independent factor on each combination of the moderator variable values will be probed.
valProbe1	The values of the first moderator that will be used to probe the effect of the independent factor.
valProbe2	The values of the second moderator that will be used to probe the effect of the independent factor.

### Details

Before using this function, researchers need to make the products of the indicators between the first-order factors using mean centering (Marsh, Wen, & Hau, 2004). Note that the double-mean centering may not be appropriate for probing interaction if researchers are interested in simple intercepts. The mean or double-mean centering can be done by the [indProd](#) function. The indicator products can be made for all possible combination or matched-pair approach (Marsh et al., 2004). Next, the hypothesized model with the regression with latent interaction will be used to fit all original indicators and the product terms. See the example for how to fit the product term below. Once the lavaan result is obtained, this function will be used to probe the interaction.

Let that the latent interaction model regressing the dependent variable ( $Y$ ) on the independent variable ( $X$ ) and two moderators ( $Z$  and  $W$ ) be

$$Y = b_0 + b_1X + b_2Z + b_3W + b_4XZ + b_5XW + b_6ZW + b_7XZW + r,$$

where  $b_0$  is the estimated intercept or the expected value of  $Y$  when  $X$ ,  $Z$ , and  $W$  are 0,  $b_1$  is the effect of  $X$  when  $Z$  and  $W$  are 0,  $b_2$  is the effect of  $Z$  when  $X$  and  $W$  is 0,  $b_3$  is the effect of  $W$  when  $X$  and  $Z$  are 0,  $b_4$  is the interaction effect between  $X$  and  $Z$  when  $W$  is 0,  $b_5$  is the interaction

effect between  $X$  and  $W$  when  $Z$  is 0,  $b_6$  is the interaction effect between  $Z$  and  $W$  when  $X$  is 0,  $b_7$  is the three-way interaction effect between  $X$ ,  $Z$ , and  $W$ , and  $r$  is the residual term.

For probing three-way interaction, the simple intercept of the independent variable at the specific values of the moderators (Aiken & West, 1991) can be obtained by

$$b_{0|X=0,Z,W} = b_0 + b_2Z + b_3W + b_6ZW.$$

The simple slope of the independent variable at the specific values of the moderators can be obtained by

$$b_{X|Z,W} = b_1 + b_3Z + b_4W + b_7ZW.$$

The variance of the simple intercept formula is

$$Var(b_{0|X=0,Z,W}) = Var(b_0) + Z^2 Var(b_2) + W^2 Var(b_3) + Z^2 W^2 Var(b_6) + 2ZCov(b_0, b_2) + 2WCov(b_0, b_3) + 2ZW$$

where  $Var$  denotes the variance of a parameter estimate and  $Cov$  denotes the covariance of two parameter estimates.

The variance of the simple slope formula is

$$Var(b_{X|Z,W}) = Var(b_1) + Z^2 Var(b_4) + W^2 Var(b_5) + Z^2 W^2 Var(b_7) + 2ZCov(b_1, b_4) + 2WCov(b_1, b_5) + 2ZW$$

Wald statistic is used for test statistic.

## Value

A list with two elements:

1. SimpleIntercept The intercepts given each value of the moderator. This element will be shown only if the factor intercept is estimated (e.g., not fixed as 0).
2. SimpleSlope The slopes given each value of the moderator.

In each element, the first column represents the values of the first moderator specified in the `valProbe1` argument. The second column represents the values of the second moderator specified in the `valProbe2` argument. The third column is the simple intercept or simple slope. The fourth column is the standard error of the simple intercept or simple slope. The fifth column is the Wald ( $z$ ) statistic. The sixth column is the  $p$ -value testing whether the simple intercepts or slopes are different from 0.

## Author(s)

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

## References

- Aiken, L. S., & West, S. G. (1991). Multiple regression: Testing and interpreting interactions. Newbury Park, CA: Sage.
- Marsh, H. W., Wen, Z., & Hau, K. T. (2004). Structural equation models of latent interactions: Evaluation of alternative estimation strategies and indicator construction. *Psychological Methods*, 9, 275-300.

**See Also**

- [indProd](#) For creating the indicator products with no centering, mean centering, double-mean centering, or residual centering.
- [probe2WayMC](#) For probing the two-way latent interaction when the results are obtained from mean-centering, or double-mean centering.
- [probe2WayRC](#) For probing the two-way latent interaction when the results are obtained from residual-centering approach.
- [probe3WayRC](#) For probing the two-way latent interaction when the results are obtained from residual-centering approach.
- [plotProbe](#) Plot the simple intercepts and slopes of the latent interaction.

**Examples**

```
library(lavaan)

dat3wayMC <- indProd(dat3way, 1:3, 4:6, 7:9)

model3 <- "
f1 =~ x1 + x2 + x3
f2 =~ x4 + x5 + x6
f3 =~ x7 + x8 + x9
f12 =~ x1.x4 + x2.x5 + x3.x6
f13 =~ x1.x7 + x2.x8 + x3.x9
f23 =~ x4.x7 + x5.x8 + x6.x9
f123 =~ x1.x4.x7 + x2.x5.x8 + x3.x6.x9
f4 =~ x10 + x11 + x12
f4 ~ f1 + f2 + f3 + f12 + f13 + f23 + f123
f1 ~~ 0*f12
f1 ~~ 0*f13
f1 ~~ 0*f123
f2 ~~ 0*f12
f2 ~~ 0*f23
f2 ~~ 0*f123
f3 ~~ 0*f13
f3 ~~ 0*f23
f3 ~~ 0*f123
f12 ~~ 0*f123
f13 ~~ 0*f123
f23 ~~ 0*f123
x1 ~ 0*1
x4 ~ 0*1
x7 ~ 0*1
x10 ~ 0*1
x1.x4 ~ 0*1
x1.x7 ~ 0*1
x4.x7 ~ 0*1
x1.x4.x7 ~ 0*1
f1 ~ NA*1
f2 ~ NA*1
f3 ~ NA*1
f12 ~ NA*1
f13 ~ NA*1
f23 ~ NA*1
f123 ~ NA*1
```

```
f4 ~ NA*1
"

fitMC3way <- sem(model3, data=dat3wayMC, meanstructure=TRUE, std.lv=FALSE)
summary(fitMC3way)

result3wayMC <- probe3WayMC(fitMC3way, c("f1", "f2", "f3", "f12", "f13", "f23", "f123"), "f4", c("f1", "f2", "f3", "f12", "f13", "f23", "f123"))
result3wayMC
```

---

probe3WayRC	<i>Probing three-way interaction on the residual-centered latent interaction</i>
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**Description**

Probing interaction for simple intercept and simple slope for the residual-centered latent three-way interaction (Pornprasertmanit, Schoemann, Geldhof, & Little, submitted)

**Usage**

```
probe3WayRC(fit, nameX, nameY, modVar, valProbe1, valProbe2)
```

**Arguments**

fit	The lavaan model object used to evaluate model fit
nameX	The vector of the factor names used as the predictors. The three first-order factors will be listed first. Then the second-order factors will be listed. The last element of the name will represent the three-way interaction. Note that the fourth element must be the interaction between the first and the second variables. The fifth element must be the interaction between the first and the third variables. The sixth element must be the interaction between the second and the third variables.
nameY	The name of factor that is used as the dependent variable.
modVar	The name of two factors that are used as the moderators. The effect of the independent factor on each combination of the moderator variable values will be probed.
valProbe1	The values of the first moderator that will be used to probe the effect of the independent factor.
valProbe2	The values of the second moderator that will be used to probe the effect of the independent factor.

**Details**

Before using this function, researchers need to make the products of the indicators between the first-order factors and residualize the products by the original indicators (Lance, 1988; Little, Bovaird, & Widaman, 2006). The process can be automated by the [indProd](#) function. Note that the indicator products can be made for all possible combination or matched-pair approach (Marsh et al., 2004). Next, the hypothesized model with the regression with latent interaction will be used to fit all original indicators and the product terms (Geldhof, Pornprasertmanit, Schoemann, & Little, in press). See the example for how to fit the product term below. Once the lavaan result is obtained, this function will be used to probe the interaction.

The probing process on residual-centered latent interaction is based on transforming the residual-centered result into the no-centered result. See Pornprasertmanit, Schoemann, Geldhof, and Little (submitted) for further details. Note that this approach based on a strong assumption that the first-order latent variables are normally distributed. The probing process is applied after the no-centered result (parameter estimates and their covariance matrix among parameter estimates) has been computed. See the [probe3WayMC](#) for further details.

## Value

A list with two elements:

1. SimpleIntercept The intercepts given each value of the moderator. This element will be shown only if the factor intercept is estimated (e.g., not fixed as 0).
2. SimpleSlope The slopes given each value of the moderator.

In each element, the first column represents the values of the first moderator specified in the `valProbe1` argument. The second column represents the values of the second moderator specified in the `valProbe2` argument. The third column is the simple intercept or simple slope. The fourth column is the standard error of the simple intercept or simple slope. The fifth column is the Wald ( $z$ ) statistic. The sixth column is the  $p$ -value testing whether the simple intercepts or slopes are different from 0.

## Author(s)

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

## References

- Geldhof, G. J., Pornprasertmanit, S., Schoemann, A., & Little, T. D. (in press). Orthogonalizing through residual centering: Applications and caveats. *Educational and Psychological Measurement*.
- Lance, C. E. (1988). Residual centering, exploratory and confirmatory moderator analysis, and decomposition of effects in path models containing interactions. *Applied Psychological Measurement*, 12, 163-175.
- Little, T. D., Bovaird, J. A., & Widaman, K. F. (2006). On the merits of orthogonalizing powered and product terms: Implications for modeling interactions. *Structural Equation Modeling*, 13, 497-519.
- Marsh, H. W., Wen, Z., & Hau, K. T. (2004). Structural equation models of latent interactions: Evaluation of alternative estimation strategies and indicator construction. *Psychological Methods*, 9, 275-300.
- Pornprasertmanit, S., Schoemann, A. M., Geldhof, G. J., & Little, T. D. (submitted). *Probing latent interaction estimated with a residual centering approach*.

## See Also

- [indProd](#) For creating the indicator products with no centering, mean centering, double-mean centering, or residual centering.
- [probe2WayMC](#) For probing the two-way latent interaction when the results are obtained from mean-centering, or double-mean centering.
- [probe3WayMC](#) For probing the three-way latent interaction when the results are obtained from mean-centering, or double-mean centering.

- [probe2WayRC](#) For probing the two-way latent interaction when the results are obtained from residual-centering approach.
- [plotProbe](#) Plot the simple intercepts and slopes of the latent interaction.

## Examples

```
library(lavaan)

dat3wayRC <- orthogonalize(dat3way, 1:3, 4:6, 7:9)

model3 <- "
f1 =~ x1 + x2 + x3
f2 =~ x4 + x5 + x6
f3 =~ x7 + x8 + x9
f12 =~ x1.x4 + x2.x5 + x3.x6
f13 =~ x1.x7 + x2.x8 + x3.x9
f23 =~ x4.x7 + x5.x8 + x6.x9
f123 =~ x1.x4.x7 + x2.x5.x8 + x3.x6.x9
f4 =~ x10 + x11 + x12
f4 ~ f1 + f2 + f3 + f12 + f13 + f23 + f123
f1 ~~ 0*f12
f1 ~~ 0*f13
f1 ~~ 0*f123
f2 ~~ 0*f12
f2 ~~ 0*f23
f2 ~~ 0*f123
f3 ~~ 0*f13
f3 ~~ 0*f23
f3 ~~ 0*f123
f12 ~~ 0*f123
f13 ~~ 0*f123
f23 ~~ 0*f123
x1 ~ 0*1
x4 ~ 0*1
x7 ~ 0*1
x10 ~ 0*1
x1.x4 ~ 0*1
x1.x7 ~ 0*1
x4.x7 ~ 0*1
x1.x4.x7 ~ 0*1
f1 ~ NA*1
f2 ~ NA*1
f3 ~ NA*1
f12 ~ NA*1
f13 ~ NA*1
f23 ~ NA*1
f123 ~ NA*1
f4 ~ NA*1
"

fitRC3way <- sem(model3, data=dat3wayRC, meanstructure=TRUE, std.lv=FALSE)
summary(fitRC3way)

result3wayRC <- probe3WayRC(fitRC3way, c("f1", "f2", "f3", "f12", "f13", "f23", "f123"), "f4", c("f1", "f2", "f3", "f12", "f13", "f23", "f123"))
result3wayRC
```



---

residualCovariate	<i>Residual centered all target indicators by covariates</i>
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---

### Description

This function will regress target variables on the covariate and replace the target variables by the residual of the regression analysis. This procedure is useful to control the covariate from the analysis model (Geldhof, Pornprasertmanit, Schoemann, & Little, in press).

### Usage

```
residualCovariate(data, targetVar, covVar)
```

### Arguments

data	The desired data to be transformed.
targetVar	Variable names or the position of indicators that users wish to be residual centered (as dependent variables)
covVar	Covariate names or the position of the covariates using for residual centering (as independent variables) onto target variables

### Value

The data that the target variables replaced by the residuals

### Author(s)

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

### References

Geldhof, G. J., Pornprasertmanit, S., Schoemann, A. M., & Little, T. D. (in press). Orthogonalizing through residual centering: Applications and caveats. *Educational and Psychological Measurement*.

### See Also

[indProd](#) For creating the indicator products with no centering, mean centering, double-mean centering, or residual centering.

### Examples

```
dat <- residualCovariate(attitude, 2:7, 1)
```

runMI

*Multiply impute and analyze data using lavaan***Description**

This function takes data with missing observations, multiple imputes the data, runs a SEM using lavaan and combines the results using Rubin's rules.

**Usage**

```
runMI(data.mat, data.model, m, miPackage="Amelia", digits=3, seed=12345,
      std.lv = FALSE, estimator = "ML", group = NULL, group.equal = "", ...)
```

**Arguments**

data.mat	Data frame with missing observations or a list of data frames where each data frame is one imputed data set (for imputed data generated outside of the function). If a list of data frames is supplied, then other options can be left at the default.
data.model	lavaan syntax for the the model to be analyzed.
m	Number of imputations wanted.
miPackage	Package to be used for imputation. Currently runMI only uses Amelia or mice for imputation.
digits	Number of digits to print in the results.
seed	Random number seed to be used in imputations.
std.lv	lavaan option. If TRUE, the metric of each latent variable is determined by fixing their variances to 1.0. If FALSE, the metric of each latent variable is determined by fixing the factor loading of the first indicator to 1.0.
estimator	lavaan option. The estimator to be used. Can be one of the following: "ML" for maximum likelihood, "GLS" for generalized least squares, "WLS" for weighted least squares (sometimes called ADF estimation), "MLM" for maximum likelihood estimation with robust standard errors and a Satorra-Bentler scaled test statistic, "MLF" for maximum likelihood estimation with standard errors based on first-order derivatives and a conventional test statistic, "MLR" for maximum likelihood estimation with robust 'Huber-White' standard errors and a scaled test statistic which is asymptotically equivalent to the Yuan-Bentler T2-star test statistic. Note that the "MLM", "MLF" and "MLR" choices only affect the standard errors and the test statistic.
group	lavaan option. A variable name in the data frame defining the groups in a multiple group analysis.
group.equal	lavaan option. A vector of character strings. Only used in a multiple group analysis. Can be one or more of the following: "loadings", "intercepts", "means", "regressions", "residuals", "residual.covariances", "lv.variances" or "lv.covariances", specifying the pattern of equality constraints across multiple groups.
...	Other arguments to be passed to the imputation package

**Value**

runMI returns a list with pooled fit indices, estimates, standard errors and fraction missing information.

fit	Pooled fit information. The first set of fit information are simply averaged across imputations and are not trustworthy. The second set of fit information, is a pooled Chi-square statistic based on Li, Meng, Raghunathan, & Rubin (1991)
parameters	Pooled parameter estimates and standard errors. Wald statistics and p values are computed from the pooled estimates and standard errors. Also contains two estimates of Fraction of Missing Information (FMI). The first estimate of FMI (FMI.1) is asymptotic FMI and the second estimate of FMI (FMI.2) is corrected for small numbers of imputation

**Author(s)**

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**References**

Li, K.H., Meng, X.-L., Raghunathan, T.E. and Rubin, D.B. (1991). Significance Levels From Repeated p-values with Multiply-Imputed Data. *Statistica Sinica*, 1, 65-92.

Rubin, D.B. (1987) *Multiple Imputation for Nonresponse in Surveys*. J. Wiley & Sons, New York.

**Examples**

```
library(lavaan)

HS.model <- ' visual =~ x1 + x2 + x3
             textual =~ x4 + x5 + x6
             speed =~ x7 + x8 + x9 '

HSMiss <- HolzingerSwineford1939[,paste("x", 1:9, sep="")]
randomMiss <- rbinom(prod(dim(HSMiss)), 1, 0.1)
randomMiss <- matrix(as.logical(randomMiss), nrow=nrow(HSMiss))
HSMiss[randomMiss] <- NA

out <- runMI(HSMiss, HS.model, m = 3)

HSMiss2 <- cbind(HSMiss, school = HolzingerSwineford1939[, "school"])
out2 <- runMI(HSMiss2, HS.model, m = 3, group="school", noms="school")

library(Amelia)

modsim <- '
f1 =~ 0.7*y1+0.7*y2+0.7*y3
f2 =~ 0.7*y4+0.7*y5+0.7*y6
f3 =~ 0.7*y7+0.7*y8+0.7*y9'
```

```

mod <- '
f1 =~ y1+y2+y3
f2 =~ y4+y5+y6
f3 =~ y7+y8+y9'

datsim <- simulateData(modsim,model.type="cfa", meanstructure=TRUE,
std.lv=TRUE, sample.nobs=c(200,200))
randomMiss2 <- rbinom(prod(dim(datsim)), 1, 0.1)
randomMiss2 <- matrix(as.logical(randomMiss2), nrow=nrow(datsim))
datsim[randomMiss2] <- NA
datsimMI <- amelia(datsim,m=3, noms="group")

out3 <- runMI(datsimMI$imputations, mod, group="group")

```

---

simParcel

---

*Simulated Data set to Demonstrate Random Allocations of Parcels*


---

### Description

A simulated data set with 2 factors with 9 indicators for each factor

### Usage

```
data(simParcel)
```

### Format

A data frame with 800 observations of 18 variables.

**f1item1** Item 1 loading on factor 1  
**f1item2** Item 2 loading on factor 1  
**f1item3** Item 3 loading on factor 1  
**f1item4** Item 4 loading on factor 1  
**f1item5** Item 5 loading on factor 1  
**f1item6** Item 6 loading on factor 1  
**f1item7** Item 7 loading on factor 1  
**f1item8** Item 8 loading on factor 1  
**f1item9** Item 9 loading on factor 1  
**f2item1** Item 1 loading on factor 2  
**f2item2** Item 2 loading on factor 2  
**f2item3** Item 3 loading on factor 2  
**f2item4** Item 4 loading on factor 2  
**f2item5** Item 5 loading on factor 2  
**f2item6** Item 6 loading on factor 2  
**f2item7** Item 7 loading on factor 2  
**f2item8** Item 8 loading on factor 2  
**f2item9** Item 9 loading on factor 2

**Source**

Data was generated using the `simsem` package.

**Examples**

```
head(simParcel)
```

---

skew	<i>Finding skewness</i>
------	-------------------------

---

**Description**

Finding skewness ( $g_1$ ) of an object

**Usage**

```
skew(object, population=FALSE)
```

**Arguments**

<code>object</code>	A vector used to find a skewness
<code>population</code>	TRUE to compute the parameter formula. FALSE to compute the sample statistic formula.

**Details**

The skewness computed is  $g_1$ . The parameter skewness  $\gamma_2$  formula is

$$\gamma_2 = \frac{\mu_3}{\mu_2^{3/2}},$$

where  $\mu_i$  denotes the  $i$  order central moment.

The excessive kurtosis formula for sample statistic  $g_2$  is

$$g_2 = \frac{k_3}{k_2^2},$$

where  $k_i$  are the  $i$  order  $k$ -statistic.

The standard error of the skewness is

$$Var(\hat{g}_2) = \frac{6}{N}$$

where  $N$  is the sample size.

**Value**

A value of a skewness with a test statistic if the population is specified as FALSE

**Author(s)**

Sunthud Pornprasertmanit (University of Kansas; <psunthud@ku.edu>)

**References**

Weisstein, Eric W. (n.d.). *Skewness*. Retrived from MathWorld—A Wolfram Web Resource <http://mathworld.wolfram.com/Skewness.html>

**See Also**

- [kurtosis](#) Find the univariate excessive kurtosis of a variable
- [mardiaSkew](#) Find the Mardia's multivariate skewness of a set of variables
- [mardiaKurtosis](#) Find the Mardia's multivariate kurtosis of a set of variables

**Examples**

```
skew(1:5)
```

---

splitSample

*Randomly Split a Data Set into Halves*


---

**Description**

This function randomly splits a data set into two halves, and saves the resulting data sets to the same folder as the original.

**Usage**

```
splitSample(dataset, path="default", div=2, type="default", name="splitSample")
```

**Arguments**

dataset	The original data set to be divided. Can be a file path to a .csv or .dat file (headers will automatically be detected) or an R object (matrix or dataframe). (Windows users: file path must be specified using FORWARD SLASHES ONLY.)
path	File path to folder for output data sets. NOT REQUIRED if dataset is a filename. Specify ONLY if dataset is an R object, or desired output folder is not that of original data set. If path is specified as "object", output data sets will be returned as a list, and not saved to hard drive.
div	Number of output data sets. NOT REQUIRED if default, 2 halves.
type	Output file format ("dat" or "csv"). NOT REQUIRED unless desired output formatting differs from that of input, or dataset is an R object and csv formatting is desired.
name	Output file name. NOT REQUIRED unless desired output name differs from that of input, or input dataset is an R object. (If input is an R object and name is not specified, name will be "splitSample".)

## Details

This function randomly orders the rows of a data set, divides the data set into two halves, and saves the halves to the same folder as the original data set, preserving the original formatting. Data set type (.csv or .dat) and formatting (headers) are automatically detected, and output data sets will preserve input type and formatting unless specified otherwise. Input can be in the form of a file path (.dat or .csv), or an R object (matrix or dataframe). If input is an R object and path is default, output data sets will be returned as a list object.

## Value

dataL                      List of output data sets. ONLY IF dataset is an R object and path is default. Otherwise, output will saved to hard drive with the same formatting as input.

## Author(s)

Corbin Quick (University of Kansas; <corbinq@ku.edu>)

## Examples

```
#### Input is .dat file
#splitSample("C:/Users/Default/Desktop/MYDATA.dat")
#### Output saved to "C:/Users/Default/Desktop/" in .dat format
#### Names are "MYDATA_s1.dat" and "MYDATA_s2.dat"

#### Input is R object
##Split C02 dataset from the datasets package
library(datasets)
splitMyData <- splitSample(C02, path="object")
summary(splitMyData[[1]])
summary(splitMyData[[2]])
#### Output object splitMyData becomes list of output data sets

#### Input is .dat file in "C:/" folder
#splitSample("C:/testdata.dat", path = "C:/Users/Default/Desktop/", type = "csv")
#### Output saved to "C:/Users/Default/Desktop/" in .csv format
#### Names are "testdata_s1.csv" and "testdata_s2.csv"

#### Input is R object
#splitSample(myData, path = "C:/Users/Default/Desktop/", name = "splitdata")
#### Output saved to "C:/Users/Default/Desktop/" in .dat format
#### Names are "splitdata_s1.dat" and "splitdata_s2.dat"
```

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