

# Package ‘OpenMx’

October 5, 2018

**Date** 2018-10-04

**Title** Extended Structural Equation Modelling

**URL** <http://openmx.ssri.psu.edu>, <https://github.com/OpenMx/OpenMx>

**BugReports** <http://openmx.ssri.psu.edu/forums>

**Description** Facilitates treatment of statistical model specifications as things that can be generated and manipulated programmatically. Structural equation models may be specified with reticular action model matrices or paths, linear structural relations matrices or paths, or directly in matrix algebra. Fit functions include full information maximum likelihood, maximum likelihood, and weighted least squares. Example models include confirmatory factor, multiple group, mixture distribution, categorical threshold, modern test theory, differential equations, state space, and many others. MacOS users can download the most up-to-date package binaries from <http://openmx.ssri.psu.edu>. See Neale, Hunter, Pritikin, Zahery, Brick, Kirkpatrick, Estabrook, Bates, Maes, & Boker (2016) <doi:10.1007/s11336-014-9435-8>.

**SystemRequirements** GNU make

**ByteCompile** yes

**License** Apache License (== 2.0)

**LinkingTo** Rcpp, RcppEigen, StanHeaders (>= 2.10.0.2), BH (>= 1.60), rpf (>= 0.45)

**Imports** Rcpp, digest, MASS, methods, Matrix, parallel

**Depends** R (>= 3.1.0)

**Suggests** mvtnorm, numDeriv, roxygen2 (>= 3.1), devtools, Rmpi, rpf (>= 0.45), snowfall, lme4

**LazyLoad** yes

**LazyData** yes

**Collate** '0ClassUnion.R' 'cache.R' 'MxBaseNamed.R' 'MxData.R' 'MxDataWLS.R' 'DefinitionVars.R' 'MxReservedNames.R' 'MxNamespace.R' 'MxSearchReplace.R' 'MxFlatSearchReplace.R'

'MxUntitled.R' 'MxAlgebraFunctions.R' 'MxExponential.R'  
'MxMatrix.R' 'DiagMatrix.R' 'FullMatrix.R' 'IdenMatrix.R'  
'LowerMatrix.R' 'SdiagMatrix.R' 'StandMatrix.R' 'SymmMatrix.R'  
'UnitMatrix.R' 'ZeroMatrix.R' 'MxMatrixFunctions.R'  
'MxAlgebra.R' 'MxCycleDetection.R' 'MxDependencies.R'  
'MxAlgebraConvert.R' 'MxAlgebraTransform.R' 'MxSquareBracket.R'  
'MxEval.R' 'MxRename.R' 'MxPath.R' 'MxObjectiveMetaData.R'  
'MxRAMMetaData.R' 'MxExpectation.R' 'MxExpectationNormal.R'  
'MxExpectationRAM.R' 'MxExpectationLISREL.R' 'MxFitFunction.R'  
'MxFitFunctionAlgebra.R' 'MxFitFunctionML.R'  
'MxFitFunctionMultigroup.R' 'MxFitFunctionRow.R'  
'MxFitFunctionWLS.R' 'MxRAMObjective.R' 'MxLISRELObjective.R'  
'MxFIMLObjective.R' 'MxMLObjective.R' 'MxRowObjective.R'  
'MxAlgebraObjective.R' 'MxBounds.R' 'MxConstraint.R'  
'MxInterval.R' 'MxTypes.R' 'MxCompute.R' 'MxModel.R'  
'MxRAMModel.R' 'MxLISRELModel.R' 'MxModelDisplay.R'  
'MxFlatModel.R' 'MxMultiModel.R' 'MxModelFunctions.R'  
'MxModelParameters.R' 'MxUnitTesting.R' 'MxApply.R' 'MxRun.R'  
'MxRunHelperFunctions.R' 'MxSummary.R' 'MxCompare.R'  
'MxSwift.R' 'MxOptions.R' 'MxThreshold.R' 'OriginalMx.R'  
'MxGraph.R' 'MxGraphviz.R' 'MxDeparse.R' 'MxCommunication.R'  
'MxRestore.R' 'MxVersion.R' 'MxPPML.R' 'MxRAMtoML.R' 'MxDiff.R'  
'MxErrorHandling.R' 'MxDetectCores.R' 'MxSaturatedModel.R'  
'omxBrownie.R' 'omxConstrainThresholds.R' 'omxGetNPSOL.R'  
'MxFitFunctionR.R' 'MxRObjective.R'  
'MxExpectationHiddenMarkov.R' 'MxExpectationMixture.R'  
'MxExpectationStateSpace.R' 'MxExpectationBA81.R'  
'MxFitFunctionGREML.R' 'MxExpectationGREML.R' 'MxMI.R'  
'MxFactorScores.R' 'MxRobustSE.R' 'MxAvailableOptimizers.R'  
'MxTryHard.R' 'MxSE.R' 'MxAutoStart.R' 'MxRetro.R' 'MxMML.R'  
'zzz.R'

**Biarch** true

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**NeedsCompilation** yes

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**Repository** CRAN

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---

as.statusCode	<i>Convert a numeric or character vector into an optimizer status code factor</i>
---------------	---

---

### Description

- 0, 'OK': Optimization succeeded
- 1, 'OK/green': Optimization succeeded, but the sequence of iterates has not yet converged (Mx status GREEN). This condition is only detected by NPSOL.
- 2, 'infeasible linear constraint': The linear constraints and bounds could not be satisfied. The problem has no feasible solution.
- 3, 'infeasible non-linear constraint': The nonlinear constraints and bounds could not be satisfied. The problem may have no feasible solution.
- 4, 'iteration limit': Optimization was stopped prematurely because the iteration limit was reached (Mx status BLUE). You might want to rerun: `m1 = mxRun(m1)` or increase the iteration limit (see [mxOption](#)).
- 5, 'not convex': The Hessian at the solution does not appear to be convex (Mx status RED). There may be more than one solution to the model. See [mxCheckIdentification](#).
- 6, 'nonzero gradient': The model does not satisfy the first-order optimality conditions to the required accuracy, and no improved point for the merit function could be found during the final linesearch (Mx status RED). To search nearby, see [mxTryHard](#).
- 7, 'bad deriv': You have provided analytic derivatives. However, your provided derivatives differ too much from numerically approximated derivatives. Double check your math.
- 9, 'internal error': An input parameter was invalid. The most likely cause is a bug in the code. Please report occurrences to developers.
- 10, 'infeasible start': Starting values were infeasible. Modify the start values for one or more parameters. For instance, set means to their measured value, or set variances and covariances to plausible values. See [mxAutoStart](#) and [mxTryHard](#).

### Usage

```
as.statusCode(code)
```

### Arguments

code                    a character or numeric vector of optimizer status code

### See Also

[mxBootstrap summary.MxModel](#)

---

BaseCompute-class	<i>BaseCompute</i>
-------------------	--------------------

---

**Description**

This is an internal class and should not be used directly.

**See Also**

[mxComputeEM](#), [mxComputeGradientDescent](#), [mxComputeHessianQuality](#), [mxComputeIterate](#), [mx-ComputeNewtonRaphson](#), [mxComputeNumericDeriv](#)

---

Bollen	<i>Bollen Data on Industrialization and Political Democracy</i>
--------	---

---

**Description**

Data set used in some of OpenMx's examples, for instance WLS. The data were reported in Bollen (1989, p. 428, Table 9.4) This set includes data from 75 developing countries each assessed on four measures of democracy measured twice (1960 and 1965), and three measures of industrialization measured once (1960).

**Usage**

```
data("Bollen")
```

**Format**

A data frame with 75 observations on the following 11 numeric variables.

- y1 Freedom of the press, 1960
- y2 Freedom of political opposition, 1960
- y3 Fairness of elections, 1960
- y4 Effectiveness of elected legislature, 1960
- y5 Freedom of the press, 1965
- y6 Freedom of political opposition, 1965
- y7 Fairness of elections, 1965
- y8 Effectiveness of elected legislature, 1965
- x1 GNP per capita, 1960
- x2 Energy consumption per capita, 1960
- x3 Percentage of labor force in industry, 1960

### Details

Variables y1-y4 and y5-y8 are typically used as indicators of the latent trait of “political democracy” in 1960 and 1965 respectively. x1-x3 are used as indicators of industrialization (1960).

### Source

The sem package (in turn, via pers. comm Bollen to Fox)

### References

Bollen, K. A. (1979). Political democracy and the timing of development. *American Sociological Review*, **44**, 572-587.

Bollen, K. A. (1980). Issues in the comparative measurement of political democracy. *American Sociological Review*, **45**, 370-390.

Bollen, K. A. (1989). *Structural equation models*. New York: Wiley-Interscience.

### Examples

```
data(Bollen)
str(Bollen)
plot(y1 ~ y2, data = Bollen)
```

---

cvectorize

*Vectorize By Column*

---

### Description

This function returns the vectorization of an input matrix in a column by column traversal of the matrix. The output is returned as a column vector.

### Usage

```
cvectorize(x)
```

### Arguments

x                    an input matrix.

### See Also

[rvectorize](#), [vech](#), [vechs](#)

### Examples

```
cvectorize(matrix(1:9, 3, 3))
cvectorize(matrix(1:12, 3, 4))
```

---

demoOneFactor

*Demonstration data for a one factor model*

---

### **Description**

Data set used in some of OpenMx's examples.

### **Usage**

```
data("demoOneFactor")
```

### **Format**

A data frame with 500 observations on the following 5 numeric variables.

x1

x2

x3

x4

x5

### **Details**

Variables x1-x5 are typically used as indicators of the latent trait.

### **Source**

Simulated.

### **References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

### **Examples**

```
data(demoOneFactor)  
cov(demoOneFactor)  
cor(demoOneFactor)
```

---

demoTwoFactor

*Demonstration data for a two factor model*

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("demoTwoFactor")
```

**Format**

A data frame with 500 observations on the following 10 numeric variables.

x1

x2

x3

x4

x5

y1

y2

y3

y4

y5

**Details**

Variables x1-x5 are typically used as indicators of one latent trait. Variables y1-y5 are typically used as indicators of another latent trait.

**Source**

Simulated.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(demoTwoFactor)  
cov(demoTwoFactor)  
cor(demoTwoFactor)
```

---

diag2vec	<i>Extract Diagonal of a Matrix</i>
----------	-------------------------------------

---

## Description

Given an input matrix, `diag2vec` returns a column vector of the elements along the diagonal.

## Usage

```
diag2vec(x)
```

## Arguments

`x` an input matrix.

## Details

Similar to the function `diag`, except that the input argument is always treated as a matrix (i.e., it doesn't have `diag()`'s functions of returning an Identity matrix from an `nrow` specification, nor to return a matrix wrapped around a diagonal if provided with a vector). To get vector2matrix functionality, call `vec2diag`.

## See Also

[vec2diag](#)

## Examples

```
diag2vec(matrix(1:9, nrow=3))
#      [,1]
# [1,]    1
# [2,]    5
# [3,]    9

diag2vec(matrix(1:12, nrow=3, ncol=4))
#      [,1]
# [1,]    1
# [2,]    5
# [3,]    9
```

---

dzfData

*DZ female data*

---

**Description**

Data for extended twin example ETC88.R

**Usage**

```
data("dzfData")
```

**Format**

A data frame with 2007 observations on the following 37 variables.

famid a numeric vector

e1 a numeric vector

e2 a numeric vector

e3 a numeric vector

e4 a numeric vector

e5 a numeric vector

e6 a numeric vector

e7 a numeric vector

e8 a numeric vector

e9 a numeric vector

e10 a numeric vector

e11 a numeric vector

e12 a numeric vector

e13 a numeric vector

e14 a numeric vector

e15 a numeric vector

e16 a numeric vector

e17 a numeric vector

e18 a numeric vector

a1 a numeric vector

a2 a numeric vector

a3 a numeric vector

a4 a numeric vector

a5 a numeric vector

a6 a numeric vector



a7 a numeric vector  
a8 a numeric vector  
a9 a numeric vector  
a10 a numeric vector  
a11 a numeric vector  
a12 a numeric vector  
a13 a numeric vector  
a14 a numeric vector  
a15 a numeric vector  
a16 a numeric vector  
a17 a numeric vector  
a18 a numeric vector

### Examples

```
data(dzfData)  
str(dzfData)
```

---

dzmData

*DZ Male data*

---

### Description

Data for extended twin example ETC88.R

### Usage

```
data("dzmData")
```

### Format

A data frame with 1990 observations on the following 37 variables.

famid a numeric vector  
e1 a numeric vector  
e2 a numeric vector  
e3 a numeric vector  
e4 a numeric vector  
e5 a numeric vector  
e6 a numeric vector  
e7 a numeric vector  
e8 a numeric vector

e9 a numeric vector  
e10 a numeric vector  
e11 a numeric vector  
e12 a numeric vector  
e13 a numeric vector  
e14 a numeric vector  
e15 a numeric vector  
e16 a numeric vector  
e17 a numeric vector  
e18 a numeric vector  
a1 a numeric vector  
a2 a numeric vector  
a3 a numeric vector  
a4 a numeric vector  
a5 a numeric vector  
a6 a numeric vector  
a7 a numeric vector  
a8 a numeric vector  
a9 a numeric vector  
a10 a numeric vector  
a11 a numeric vector  
a12 a numeric vector  
a13 a numeric vector  
a14 a numeric vector  
a15 a numeric vector  
a16 a numeric vector  
a17 a numeric vector  
a18 a numeric vector

**Examples**

```
data(dzmData)  
str(dzmData)
```

---

dzoData	<i>DZ opposite sex data</i>
---------	-----------------------------

---

**Description**

Data for extended twin example ETC88.R

**Usage**

```
data("dzoData")
```

**Format**

A data frame with 3981 observations on the following 37 variables.

famid a numeric vector

e1 a numeric vector

e2 a numeric vector

e3 a numeric vector

e4 a numeric vector

e5 a numeric vector

e6 a numeric vector

e7 a numeric vector

e8 a numeric vector

e9 a numeric vector

e10 a numeric vector

e11 a numeric vector

e12 a numeric vector

e13 a numeric vector

e14 a numeric vector

e15 a numeric vector

e16 a numeric vector

e17 a numeric vector

e18 a numeric vector

a1 a numeric vector

a2 a numeric vector

a3 a numeric vector

a4 a numeric vector

a5 a numeric vector

a6 a numeric vector

a7 a numeric vector  
a8 a numeric vector  
a9 a numeric vector  
a10 a numeric vector  
a11 a numeric vector  
a12 a numeric vector  
a13 a numeric vector  
a14 a numeric vector  
a15 a numeric vector  
a16 a numeric vector  
a17 a numeric vector  
a18 a numeric vector

### Examples

```
data(dzoData)  
str(dzoData)
```

---

eigenvec

*Eigenvector/Eigenvalue Decomposition*

---

### Description

`eigenval` computes the real parts of the eigenvalues of a square matrix. `eigenvec` computes the real parts of the eigenvectors of a square matrix. `ieigenval` computes the imaginary parts of the eigenvalues of a square matrix. `ieigenvec` computes the imaginary parts of the eigenvectors of a square matrix. `eigenval` and `ieigenval` return  $n \times 1$  matrices containing the real or imaginary parts of the eigenvalues, sorted in decreasing order of the modulus of the complex eigenvalue. For eigenvalues without an imaginary part, this is equivalent to sorting in decreasing order of the absolute value of the eigenvalue. (See [Mod](#) for more info.) `eigenvec` and `ieigenvec` return  $n \times n$  matrices, where each column corresponds to an eigenvector. These are sorted in decreasing order of the modulus of their associated complex eigenvalue.

### Usage

```
eigenval(x)  
eigenvec(x)  
ieigenval(x)  
ieigenvec(x)
```

### Arguments

x the square matrix whose eigenvalues/vectors are to be calculated.

**Details**

Eigenvectors returned by `eigenvec` and `ieigenvec` are normalized to unit length.

**See Also**

[eigen](#)

**Examples**

```
A <- mxMatrix(values = runif(25), nrow = 5, ncol = 5, name = 'A')
G <- mxMatrix(values = c(0, -1, 1, -1), nrow=2, ncol=2, name='G')

model <- mxModel(A, G, name = 'model')

mxEval(eigenvec(A), model)
mxEval(eigenvec(G), model)
mxEval(eigenval(A), model)
mxEval(eigenval(G), model)
mxEval(ieigenvec(A), model)
mxEval(ieigenvec(G), model)
mxEval(ieigenval(A), model)
mxEval(ieigenval(G), model)
```

---

example1

*Bivariate twin data example from Classic Mx Manual*

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("example1")
```

**Format**

A data frame with 400 observations on the following variables.

IDNum Twin pair ID  
Zygosity Zygosity of the twin pair  
X1 X variable for twin 1  
Y1 Y variable for twin 1  
X2 X variable for twin 2  
Y2 Y variable for twin 2

**Details**

Same as [example2](#) but in wide format instead of tall.

**Source**

Classic Mx Manual.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(example1)
plot(X2 ~ X1, data=example1)
```

---

example2

*Bivariate twin data example from Classic Mx Manual*

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("example2")
```

**Format**

A data frame with 800 observations on the following variables.

IDNum ID number

TwinNum Twin ID number

Zygoty Zygoty of the twin

X X variable for twins 1 and 2

Y Y variable for twins 1 and 2

**Details**

Same as [example1](#) but in tall format instead of wide.

**Source**

Classic Mx Manual.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(example2)
plot(Y ~ X, data=example2)
```

---

expm

*Matrix exponential*

---

**Description**

Matrix exponential

**Usage**

```
expm(x)
```

**Arguments**

x                    matrix

---

factorExample1

*Example Factor Analysis Data*

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("factorExample1")
```

**Format**

A data frame with 500 observations on the following variables.

x1

x2

x3

x4

x5

x6

x7

x8

x9

**Details**

This appears to be a three factor model, but perhaps with an odd loading structure.

**Source**

Simulated

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(factorExample1)
round(cor(factorExample1), 2)

factanal(covmat=cov(factorExample1), factors=3, rotation="promax")
```

---

factorScaleExample1    *Example Factor Analysis Data for Scaling the Model*

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("factorScaleExample1")
```

**Format**

A data frame with 200 observations on the following variables.

X1  
X2  
X3  
X4  
X5  
X6  
X7  
X8  
X9  
X10  
X11  
X12



**Details**

This appears to be a three factor model with factor 1 loading on X1-X4, factor 2 on X5-X8, and factor 3 on X9-X12.

**Source**

Simulated

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(factorScaleExample1)
round(cor(factorScaleExample1), 2)
```

---

factorScaleExample2    *Example Factor Analysis Data for Scaling the Model*

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("factorScaleExample2")
```

**Format**

A data frame with 200 observations on the following variables.

X1

X2

X3

X4

X5

X6

X7

X8

X9

X10

X11

X12

**Details**

This appears to be a three factor model with factor 1 loading on X1-X4, factor 2 on X5-X8, and factor 3 on X9-X12. It differs from [factorScaleExample1](#) in the scaling of the variables.

**Source**

Simulated

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(factorScaleExample2)
round(cor(factorScaleExample2), 2)

data(factorScaleExample2)
plot(sapply(factorScaleExample1, var), type='l', ylim=c(0, 6), lwd=3)
lines(1:12, sapply(factorScaleExample2, var), col='blue', lwd=3)
```

---

*genericFitDependencies, MxBaseFitFunction-method*  
*Add dependencies*

---

**Description**

If there is an expectation, then the fitfunction should always depend on it. Hence, subclasses that implement this method must ignore the passed-in dependencies and use "dependencies <- callNextMethod()" instead.

**Usage**

```
## S4 method for signature 'MxBaseFitFunction'
genericFitDependencies(.Object, flatModel,
  dependencies)
```

**Arguments**

<code>.Object</code>	fit function object
<code>flatModel</code>	flat model that lives with <code>.Object</code>
<code>dependencies</code>	accumulated dependency relationships

---

HS.ability.data	<i>Holzinger and Swineford (1939) Ability data in 301 children from two schools</i>
-----------------	---

---

### Description

This classic data set contains of intelligence-test scores from 301 children on 26 distinct tests. The data are also available in the MBESS package.

The tests cover mental speed, memory, mathematical-ability, spatial, and verbal ability as listed below.

### Usage

```
data("HS.ability.data")
```

### Format

A data frame with 301 observations on the following 2 variables.

id student ID number (int)  
 Gender Sex (Factor w/ 2 levels "Female", "Male")  
 grade Grade in school (integer 7 or 8)  
 agey Age in years (integer)  
 agem Age in months (integer)  
 school School attended (Factor w/2 levels "Grant-White" and "Pasteur")  
 addition A speed test (numeric)  
 code A speed test (numeric)  
 counting A speed test (numeric)  
 straight A speed test (numeric)  
 wordr A memory subtest  
 numberr A memory subtest  
 figurer A memory subtest  
 object A memory subtest  
 numberf A memory subtest  
 figurew A memory subtest  
 deduct A mathematical subtest  
 numeric A mathematical subtest  
 problemr A mathematical subtest  
 series A mathematical subtest  
 arithmet A mathematical subtest  
 visual A spatial subtest

cubes A spatial subtest  
paper A spatial subtest  
flags A spatial subtest  
paperrev A spatial subtest  
flagssub A spatial subtest  
general A verbal subtest  
paragrap A verbal subtest  
sentence A verbal subtest  
wordc A verbal subtest  
wordm A verbal subtest

### Details

The data are from children who differ in grade (seventh- and eighth-grade) and are nested in one of two schools (Pasteur and Grant-White). You will see it in use elsewhere, both in R (lavaan, MBESS), and in Joreskog (1969) reporting a cfa on the Grant-White school subject subset).

The last two tests are substitute versions for other tests. paperrev (a paper form board test) can substitute for paper and flagssub for the lozenges test flags.

### Source

Holzinger, K., and Swineford, F. (1939).

### References

Holzinger, K., and Swineford, F. (1939). A study in factor analysis: The stability of a bifactor solution. *Supplementary Educational Monograph*, no. **48**. Chicago: University of Chicago Press.  
Joreskog, K. G. (1969). A general approach to confirmatory maximum likelihood factor analysis. *Psychometrika*, **34**, 183-202.

### Examples

```
data(HS.ability.data)
str(HS.ability.data)
levels(HS.ability.data$school)
plot(flags ~ flagssub, data = HS.ability.data)
```

---

imxAddDependency	<i>Add a dependency</i>
------------------	-------------------------

---

**Description**

The dependency tracking system ensures that algebra and fitfunctions are not recomputed if their inputs have not changed. Dependency information is computed prior to handing the model off to the optimizer to reduce overhead during optimization.

**Usage**

```
imxAddDependency(source, sink, dependencies)
```

**Arguments**

source	a character vector of the names of the computation sources (inputs)
sink	the name of the computation sink (output)
dependencies	the dependency graph

**Details**

Each free parameter keeps track of all the objects that store that free parameter and the transitive closure of all algebras and fit functions that depend on that free parameter. Similarly, each definition variable keeps track of all the objects that store that free parameter and the transitive closure of all the algebras and fit functions that depend on that free parameter. At each iteration of the optimization, when the free parameter values are updated, all of the dependencies of that free parameter are marked as dirty (see `omxFitFunction.repopulateFun`). After an algebra or fit function is computed, `omxMarkClean()` is called to indicate that the algebra or fit function is updated. Similarly, when definition variables are populated in FIML, all of the dependencies of the definition variables are marked as dirty. Particularly for FIML, the fact that non-definition-variable dependencies remain clean is a big performance gain.

---

imxAutoOptionValue	<i>imxAutoOptionValue</i>
--------------------	---------------------------

---

**Description**

Convert "Auto" placeholders in global mxOptions to actual default values.

**Usage**

```
imxAutoOptionValue(optionName, optionList = options())$mxOption)
```

**Arguments**

optionName	Character string naming the <a href="#">mxOption</a> for which a numeric or integer value is wanted.
optionList	List of options; defaults to list of global <a href="#">mxOptions</a> . <code>imxAutoOptionValue</code>

**Details**

This is an internal function exported for documentation purposes. Its primary purpose is to convert the on-load value of "Auto" to valid values for [mxOptions](#) 'Gradient step size', 'Gradient iterations', and 'Function precision'—respectively, 1.0e-7, 1L, and 1e-14.

---

<code>imxCheckMatrices</code>	<i>imxCheckMatrices</i>
-------------------------------	-------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxCheckMatrices(model)
```

**Arguments**

model	model
-------	-------

---

<code>imxCheckVariables</code>	<i>imxCheckVariables</i>
--------------------------------	--------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxCheckVariables(flatModel, namespace)
```

**Arguments**

flatModel	flatModel
namespace	namespace

---

imxConDecMatrixSlots    *Condense/decondense slots of an MxMatrix*

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxConDecMatrixSlots(object)
```

**Arguments**

object                    of class MxMatrix

---

imxConstraintRelations  
                          *imxConstraintRelations*

---

**Description**

A string vector of valid constraint binary relations.

**Usage**

```
imxConstraintRelations
```

**Format**

An object of class character of length 3.

---

imxConvertIdentifier    *imxConvertIdentifier*

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxConvertIdentifier(identifiers, modelname, namespace, strict = FALSE)
```

**Arguments**

identifiers	identifiers
modelname	modelname
namespace	namespace
strict	strict

---

<code>imxConvertLabel</code>	<i>imxConvertLabel</i>
------------------------------	------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxConvertLabel(label, modelname, dataname, namespace)
```

**Arguments**

label	label
modelname	modelname
dataname	dataname
namespace	namespace

---

<code>imxConvertSubstitution</code>	<i>imxConvertSubstitution</i>
-------------------------------------	-------------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxConvertSubstitution(substitution, modelname, namespace)
```

**Arguments**

substitution	substitution
modelname	modelname
namespace	namespace



---

imxCreateMatrix	<i>Create a matrix</i>
-----------------	------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxCreateMatrix(.Object, labels, values, free, lbound, ubound, nrow, ncol,
  byrow, name, condenseSlots, joinKey, joinModel)
```

**Arguments**

.Object	the matrix
labels	labels
values	values
free	free
lbound	lbound
ubound	ubound
nrow	nrow
ncol	ncol
byrow	byrow
name	name
condenseSlots	condenseSlots
joinKey	joinKey
joinModel	joinModel

---

imxDataTypes	<i>Valid types of data that can be contained by MxData</i>
--------------	--

---

**Description**

Valid types of data that can be contained by MxData

**Usage**

```
imxDataTypes
```

**Format**

An object of class character of length 5.

---

imxDefaultGetSlotDisplayNames  
*imxDefaultGetSlotDisplayNames*

---

### Description

Returns a list of display-friendly object slot names This is an internal function exported for those people who know what they are doing.

### Usage

```
imxDefaultGetSlotDisplayNames(x, pattern = ".*")
```

### Arguments

x	The object from which to get slot names
pattern	Initial pattern to match (default of '.*' matches any)

---

imxDeparse                      *Deparse for MxObjects*

---

### Description

Deparse for MxObjects

### Usage

```
imxDeparse(object, indent = "  ")
```

### Arguments

object	object
indent	indent

---

imxDependentModels     *Are submodels dependence?*

---

**Description**

Are submodels dependence?

**Usage**

imxDependentModels(model)

**Arguments**

model                    model

---

imxDetermineDefaultOptimizer

*imxDetermineDefaultOptimizer*

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

imxDetermineDefaultOptimizer()

**Details**

Returns a character, the default optimizer

---

imxDiff

*Set difference on regular types or S4 objects*

---

**Description**

Set difference on regular types or S4 objects

**Usage**

imxDiff(a, b, slots = c("setequal", "intersect"))

**Arguments**

a	a
b	b
slots	slots

---

<code>imxDmnorm</code>	<i>A C implementation of dmnorm</i>
------------------------	-------------------------------------

---

**Description**

This API is visible to permit testing. Please do not use.

**Usage**

```
imxDmnorm(loc, mean, sigma)
```

**Arguments**

<code>loc</code>	<code>loc</code>
<code>mean</code>	<code>mean</code>
<code>sigma</code>	<code>sigma</code>

---

<code>imxEvalByName</code>	<i>imxEvalByName</i>
----------------------------	----------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxEvalByName(name, model, compute = FALSE, show = FALSE)
```

**Arguments**

<code>name</code>	<code>name</code>
<code>model</code>	<code>model</code>
<code>compute</code>	<code>compute</code>
<code>show</code>	<code>show</code>

**Details**

This function should not be used in MxSummary. All summary information should be extracted from runstate.

---

imxExtractMethod	<i>imxExtractMethod</i>
------------------	-------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxExtractMethod(model, index)
```

**Arguments**

model	model
index	index

---

imxExtractNames	<i>imxExtractNames</i>
-----------------	------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxExtractNames(lst)
```

**Arguments**

lst	lst
-----	-----

---

imxExtractReferences	<i>imxExtractReferences</i>
----------------------	-----------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxExtractReferences(lst)
```

**Arguments**

lst	lst
-----	-----

---

imxExtractSlot	<i>imxExtractSlot</i>
----------------	-----------------------

---

**Description**

Checks for and extracts a slot from the object This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxExtractSlot(x, name)
```

**Arguments**

x	The object
name	the name of the slot

---

imxFlattenModel	<i>Remove heirarchical structure from model</i>
-----------------	---

---

**Description**

Remove heirarchical structure from model

**Usage**

```
imxFlattenModel(model, namespace, unsafe = FALSE)
```

**Arguments**

model	model
namespace	namespace
unsafe	whether to skip sanity checks

---

imxFreezeModel	<i>Freeze model</i>
----------------	---------------------

---

**Description**

Remove free parameters and fit function from model.

**Usage**

```
imxFreezeModel(model)
```

**Arguments**

model	model
-------	-------

---

imxGenerateLabels	<i>imxGenerateLabels</i>
-------------------	--------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxGenerateLabels(model)
```

**Arguments**

model	model
-------	-------

---

imxGenerateNamespace	<i>imxGenerateNamespace</i>
----------------------	-----------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxGenerateNamespace(model)
```

**Arguments**

model	model
-------	-------

---

 imxGenericModelBuilder

*imxGenericModelBuilder*


---

### Description

This is an internal function exported for those people who know what they are doing.

### Usage

```
imxGenericModelBuilder(model, lst, name, manifestVars, latentVars, submodels,
  remove, independent)
```

### Arguments

model	model
lst	lst
name	name
manifestVars	manifestVars
latentVars	latentVars
submodels	submodels
remove	remove
independent	independent

---

 imxGenSwift

*imxGenSwift*


---

### Description

This is an internal function exported for those people who know what they are doing.

### Usage

```
imxGenSwift(tc, sites, sfile)
```

### Arguments

tc	tc
sites	sites
sfile	sfile



---

imxGentleResize	<i>Resize an MxMatrix while preserving entries</i>
-----------------	--

---

**Description**

Resize an MxMatrix while preserving entries

**Usage**

```
imxGentleResize(matrix, dimnames)
```

**Arguments**

matrix	the MxMatrix to resize
dimnames	desired dimnames for the new matrix

**Value**

a resized MxMatrix

**Examples**

```
m1 <- mxMatrix(values=1:9, nrow=3, ncol=3,
               dimnames=list(paste0('r',1:3), paste0('c',1:3)))

imxGentleResize(m1, dimnames=list(paste0('r',c(1,3,5)),
                                   paste0('c',c(2,4,6))))
```

---

imxGetNumThreads	<i>imxGetNumThreads</i>
------------------	-------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxGetNumThreads()
```

---

 imxGetSlotDisplayNames

*imxGetSlotDisplayNames*


---

### Description

Returns a list of display-friendly object slot names This is an internal function exported for those people who know what they are doing.

### Usage

```
imxGetSlotDisplayNames(object, pattern = ".*", slotList = slotNames(object),
  showDots = FALSE, showEmpty = FALSE)
```

### Arguments

object	The object from which to get slot names
pattern	Initial pattern to match (default of '.*' matches any)
slotList	List of slots for which to get display names (default = slotNames(object), i.e., all)
showDots	Include slots whose names start with '.' (default FALSE)
showEmpty	Include slots with length-zero contents (default FALSE)

---

 imxHasConstraint

*imxHasConstraint*


---

### Description

This is an internal function exported for those people who know what they are doing. This function checks if a model (or its submodels) has at least one MxConstraint.

### Usage

```
imxHasConstraint(model)
```

### Arguments

model	model
-------	-------

---

```
imxHasDefinitionVariable
    imxHasDefinitionVariable
```

---

**Description**

This is an internal function exported for those people who know what they are doing. This function checks if a model (or its submodels) has at least one definition variable.

**Usage**

```
imxHasDefinitionVariable(model)
```

**Arguments**

```
model          model
```

---

```
imxHasNPSOL    imxHasNPSOL
```

---

**Description**

```
imxHasNPSOL
```

**Usage**

```
imxHasNPSOL()
```

**Value**

Returns TRUE if the NPSOL proprietary optimizer is compiled and linked with OpenMx. Otherwise FALSE.

---

```
imxHasOpenMP   imxHasOpenMP
```

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxHasOpenMP()
```

---

<code>imxHasThresholds</code>	<i>imxHasThresholds</i>
-------------------------------	-------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing. This function checks if a model (or its submodels) has any thresholds.

**Usage**

```
imxHasThresholds(model)
```

**Arguments**

<code>model</code>	<code>model</code>
--------------------	--------------------

---

<code>imxIdentifier</code>	<i>imxIdentifier</i>
----------------------------	----------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxIdentifier(namespace, name)
```

**Arguments**

<code>namespace</code>	<code>namespace</code>
<code>name</code>	<code>name</code>

---

<code>imxIndependentModels</code>	<i>Are submodels independent?</i>
-----------------------------------	-----------------------------------

---

**Description**

Are submodels independent?

**Usage**

```
imxIndependentModels(model)
```

**Arguments**

<code>model</code>	<code>model</code>
--------------------	--------------------

---

imxInitModel	<i>imxInitModel</i>
--------------	---------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxInitModel(model)
```

**Arguments**

model	model
-------	-------

---

imxIsDefinitionVariable	<i>imxIsDefinitionVariable</i>
-------------------------	--------------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxIsDefinitionVariable(name)
```

**Arguments**

name	name
------	------

---

imxIsPath	<i>imxIsPath</i>
-----------	------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxIsPath(value)
```

**Arguments**

value	value
-------	-------

---

`imxJiggle`*imxJiggle*

---

**Description**

Jiggle parameter values, subject to box constraints. For internal use by `mxTryHard()`. This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxJiggle(params, lbounds, ubounds, dsn, loc, scale)
```

**Arguments**

<code>params</code>	Numeric vector of current free parameter values.
<code>lbounds</code>	Numeric vector of lower bounds on parameters.
<code>ubounds</code>	Numeric vector of upper bounds on parameters.
<code>dsn</code>	Character string naming the family of distribution to be used.
<code>loc</code>	Numeric vector of location parameters (medians).
<code>scale</code>	Numeric vector of scale parameters (see source code).

---

`imxLocateFunction`*imxLocateFunction*

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxLocateFunction(function_name)
```

**Arguments**

<code>function_name</code>	<code>function_name</code>
----------------------------	----------------------------

---

imxLocateIndex	<i>imxLocateIndex</i>
----------------	-----------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxLocateIndex(model, name, referant)
```

**Arguments**

model	model
name	name
referant	referant

---

imxLocateLabel	<i>imxLocateLabel</i>
----------------	-----------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxLocateLabel(label, model, parameter)
```

**Arguments**

label	label
model	model
parameter	parameter

---

imxLog	<i>Test thread-safe output code</i>
--------	-------------------------------------

---

**Description**

This is the code that the backend uses to write diagnostic information to standard error. This function should not be called from R. We make it available only for testing.

**Usage**

```
imxLog(str)
```

**Arguments**

str	the character string to output
-----	--------------------------------

---

imxLookupSymbolTable	<i>imxLookupSymbolTable</i>
----------------------	-----------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxLookupSymbolTable(name)
```

**Arguments**

name	name
------	------

---

imxModelBuilder	<i>imxModelBuilder</i>
-----------------	------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxModelBuilder(model, lst, name, manifestVars, latentVars, submodels, remove,
  independent)
```



**Arguments**

model	model
lst	lst
name	name
manifestVars	manifestVars
latentVars	latentVars
submodels	submodels
remove	remove
independent	independent

**Details**

TODO: It probably makes sense to split this into separate methods. For example, modelAddVariables and modelRemoveVariables could be their own methods. This would reduce some cut&paste duplication.

---

imxModelTypes	<i>imxModelTypes</i>
---------------	----------------------

---

**Description**

A list of supported model types

**Usage**

```
imxModelTypes
```

**Format**

An object of class `list` of length 3.

---

imxMpiWrap	<i>imxMpiWrap</i>
------------	-------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxMpiWrap(fun)
```

**Arguments**

fun	fun
-----	-----

---

imxOriginalMx	<i>imxOriginalMx</i>
---------------	----------------------

---

### Description

This is an internal function exported for those people who know what they are doing.

### Usage

```
imxOriginalMx(mx.filename, output.directory)
```

### Arguments

mx.filename	mx.filename
output.directory	output.directory

---

imxPPML	<i>imxPPML</i>
---------	----------------

---

### Description

Potentially enable the PPML optimization for the given model.

### Usage

```
imxPPML(model, flag = TRUE)
```

### Arguments

model	the MxModel to evaluate
flag	whether to potentially enable PPML

---

`imxPPML.Test.Battery` *imxPPML.Test.Battery*

---

## Description

PPML can be applied to a number of special cases. This function will test the given model for all of these special cases.

## Usage

```
imxPPML.Test.Battery(model, verbose = FALSE, testMissingness = TRUE,  
  testPermutations = TRUE, testEstimates = TRUE, testFakeLatents = TRUE,  
  tolerances = c(0.001, 0.001, 0.001))
```

## Arguments

<code>model</code>	the model to test
<code>verbose</code>	whether to print diagnostics
<code>testMissingness</code>	try with missingness
<code>testPermutations</code>	try with permutations
<code>testEstimates</code>	examine estimates
<code>testFakeLatents</code>	try with fake latents
<code>tolerances</code>	a vector of tolerances

## Details

Requirements for model passed to this function: - Path-specified - Means vector must be present - Covariance data (with data means vector) - (Recommended) All error variances should be specified on the diagonal of the S matrix, and not as a latent with a loading only on to that manifest

Function will test across all permutations of: - Covariance vs Raw data - Means vector present vs Means vector absent - Path versus Matrix specification - All orders of permutations of latents with manifests

---

imxPPML.Test.Test	<i>imxPPML.Test.Test</i>
-------------------	--------------------------

---

**Description**

Test that PPML solutions match non-PPML solutions.

**Usage**

```
imxPPML.Test.Test(model, checkLL = TRUE, checkByName = FALSE,
  tolerance = 0.5, testEstimates = TRUE)
```

**Arguments**

model	the MxModel to evaluate
checkLL	whether to check log likelihood
checkByName	check values using their names
tolerance	closeness tolerance for check
testEstimates	whether to test for the same parameter estimates

**Details**

This is an internal function used for comparing PPML and non-PPML solutions. Generally, non-developers will not use this function.

---

imxPreprocessModel	<i>imxPreprocessModel</i>
--------------------	---------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxPreprocessModel(model)
```

**Arguments**

model	model
-------	-------

---

<code>imxReplaceMethod</code>	<i>imxReplaceMethod</i>
-------------------------------	-------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxReplaceMethod(x, name, value)
```

**Arguments**

<code>x</code>	the thing
<code>name</code>	name
<code>value</code>	value

---

<code>imxReplaceModels</code>	<i>Replace parts of a model</i>
-------------------------------	---------------------------------

---

**Description**

Replace parts of a model

**Usage**

```
imxReplaceModels(model, replacements)
```

**Arguments**

<code>model</code>	model
<code>replacements</code>	replacements

---

imxReplaceSlot	<i>imxReplaceSlot</i>
----------------	-----------------------

---

**Description**

Checks for and replaces a slot from the object This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxReplaceSlot(x, name, value, check = TRUE)
```

**Arguments**

x	object
name	the name of the slot
value	replacement value
check	Check replacement value for validity (default TRUE)

---

imxReportProgress	<i>Report backend progress</i>
-------------------	--------------------------------

---

**Description**

Prints a show status string to the console without emitting a newline.

**Usage**

```
imxReportProgress(info, eraseLen)
```

**Arguments**

info	the character string to print
eraseLen	the number of characters to erase

**Examples**

```
library(OpenMx)

previousLen <- 0

easyReportProcess <- function(msg) {
  imxReportProgress(msg, previousLen)
  previousLen <- nchar(msg)
}
```

```
demo <- function() {  
  easyReportProcess("abc123")  
  Sys.sleep(1)  
  easyReportProcess("this is much longer")  
  Sys.sleep(1)  
  easyReportProcess("this is short")  
  Sys.sleep(1)  
  easyReportProcess("almost done")  
  Sys.sleep(1)  
  easyReportProcess("")  
  cat("DONE!", fill=TRUE)  
}  
  
## Not run: demo()
```

---

imxReservedNames	<i>imxReservedNames</i>
------------------	-------------------------

---

**Description**

Vector of reserved names

**Usage**

```
imxReservedNames
```

**Format**

An object of class character of length 7.

---

imxReverseIdentifier	<i>imxReverseIdentifier</i>
----------------------	-----------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxReverseIdentifier(model, name)
```

**Arguments**

model	model
name	name

---

 imxRobustSE

*imxRobustSE*


---

### Description

This is an internal function exported for those people who know what they are doing.

### Usage

```
imxRobustSE(model, details = FALSE)
```

### Arguments

model	An OpenMx model object that has been run
details	logical. whether to return the full parameter covariance matrix

### Details

This function computes robust standard errors via a sandwich estimator. The "bread" of the sandwich is the numerically computed inverse Hessian of the likelihood function. This is what is typically used for standard errors throughout OpenMx. The "meat" of the sandwich is proportional to the covariance matrix of the numerically computed row derivatives of the likelihood function (i.e. row gradients).

When `details=FALSE`, only the standard errors are returned.

When `details=TRUE`, a list with five named elements is returned. Element `SE` is the vector of standard errors that is also returned when `details=FALSE`. Element `cov` is the full robust covariance matrix of the parameter estimates; the square root of the diagonal of `cov` gives the standard errors. Element `bread` is the aforementioned "bread"—the naive (non-robust) covariance matrix of the parameter estimates. Element `meat` is the aforementioned "meat," proportional to the covariance matrix of the row gradients. Element `TIC` is the model's Takeuchi Information Criterion, which is a generalization of AIC calculated from the "bread," the "meat," and the loglikelihood at the maximum-likelihood solution.

This function does not work correctly with multigroup models in which the groups themselves contain subgroups. This function also does not correctly handle multilevel data.

---

 imxRowGradients

*imxRowGradients*


---

### Description

This is an internal function exported for those people who know what they are doing.

### Usage

```
imxRowGradients(model, robustSE = FALSE)
```



**Arguments**

model	An OpenMx model object that has been run
robustSE	Logical; are the row gradients being requested to calculate robust standard errors?

**Details**

This function computes the gradient for each row of data. The returned object is a matrix with the same number of rows as the data, and the same number of columns as there are free parameters.

---

imxSameType	<i>imxSameType</i>
-------------	--------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxSameType(a, b)
```

**Arguments**

a	a
b	b

---

imxSeparatorChar	<i>imxSeparatorChar</i>
------------------	-------------------------

---

**Description**

The character between the model name and the named entity inside the model.

**Usage**

```
imxSeparatorChar
```

**Format**

An object of class character of length 1.

---

imxSfClient	<i>imxSfClient</i>
-------------	--------------------

---

**Description**

As of snowfall 1.84, the snowfall supervisor process stores an internal state information in a variable named ".sfOption" that is located in the "snowfall" namespace. The snowfall client processes store internal state information in a variable named ".sfOption" that is located in the global namespace.

**Usage**

```
imxSfClient()
```

**Details**

As long as the previous statement is true, then the current process is a snowfall client if-and-only-if exists(".sfOption").

---

imxSimpleRAMPredicate	<i>imxSimpleRAMPredicate</i>
-----------------------	------------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxSimpleRAMPredicate(model)
```

**Arguments**

model	model
-------	-------

---

imxSparseInvert	<i>Sparse symmetric matrix invert</i>
-----------------	---------------------------------------

---

**Description**

This API is visible to permit testing. Please do not use.

**Usage**

```
imxSparseInvert(mat)
```

**Arguments**

mat	the matrix to invert
-----	----------------------

---

imxSquareMatrix	<i>imxSquareMatrix</i>
-----------------	------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxSquareMatrix(.Object)
```

**Arguments**

.Object	.Object
---------	---------

---

imxSymmetricMatrix	<i>imxSymmetricMatrix</i>
--------------------	---------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxSymmetricMatrix(.Object)
```

**Arguments**

.Object	.Object
---------	---------

---

imxTypeName	<i>imxTypeName</i>
-------------	--------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxTypeName(model)
```

**Arguments**

model	model
-------	-------

---

<code>imxUntitledName</code>	<i>imxUntitledName</i>
------------------------------	------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxUntitledName()
```

**Details**

Returns a character, the name of the next untitled entity

---

<code>imxUntitledNumber</code>	<i>imxUntitledNumber</i>
--------------------------------	--------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxUntitledNumber()
```

**Details**

Increments the untitled number counter and returns its value

---

<code>imxUntitledNumberReset</code>	<i>imxUntitledNumberReset</i>
-------------------------------------	-------------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxUntitledNumberReset()
```

**Details**

Resets the [imxUntitledNumber](#) counter

---

`imxUpdateModelValues`    *imxUpdateModelValues*

---

**Description**

Deprecated. This function does not handle parameters with equality constraints. Do not use.

**Usage**

`imxUpdateModelValues(model, flatModel, values)`

**Arguments**

<code>model</code>	model
<code>flatModel</code>	flat model
<code>values</code>	values to update

---

`imxVariableTypes`    *imxVariableTypes*

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

`imxVariableTypes`

**Format**

An object of class character of length 2.

**Details**

The acceptable variable types

---

<code>imxVerifyMatrix</code>	<i>imxVerifyMatrix</i>
------------------------------	------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxVerifyMatrix(.Object)
```

**Arguments**

<code>.Object</code>	<code>.Object</code>
----------------------	----------------------

---

<code>imxVerifyModel</code>	<i>imxVerifyModel</i>
-----------------------------	-----------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxVerifyModel(model)
```

**Arguments**

<code>model</code>	<code>model</code>
--------------------	--------------------

---

<code>imxVerifyName</code>	<i>imxVerifyName</i>
----------------------------	----------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxVerifyName(name, stackNumber)
```

**Arguments**

<code>name</code>	<code>name</code>
<code>stackNumber</code>	<code>stackNumber</code>

---

imxVerifyReference	<i>imxVerifyReference</i>
--------------------	---------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
imxVerifyReference(reference, stackNumber)
```

**Arguments**

reference	reference
stackNumber	stackNumber

---

imxWlsChiSquare	<i>Calculate Chi Square for a WLS Model</i>
-----------------	---

---

**Description**

This is an internal function used to calculate the Chi Square distributed fit statistic for weighted least squares models.

**Usage**

```
imxWlsChiSquare(model, J=NA)
```

**Arguments**

model	An MxModel object with acov (WLS) data
J	Optional pre-computed Jacobian matrix

**Details**

The Chi Square fit statistic for models fit with maximum likelihood depends on the difference in model fit in minus two log likelihood units between the saturated model and the more restricted model under investigation. For models fit with weighted least squares a different expression is required. If  $J$  is the first derivative (Jacobian) of the mapping from the free parameters to the unique elements of the expected covariance, means, and thresholds,  $J_c$  is the orthogonal complement of  $J$ ,  $W$  is the inverse of the full weight matrix, and  $e$  is the difference between the sample-estimated and model-implied covariance, means, and thresholds, then the Chi Square fit statistic is

$$\chi^2 = e' J_c (J_c' W J_c)^{-1} J_c' e$$





**Details**

The standard errors for models fit with maximum likelihood are related to the second derivative (Hessian) of the likelihood function with respect to the free parameters. For models fit with weighted least squares a different expression is required. If  $J$  is the first derivative (Jacobian) of the mapping from the free parameters to the unique elements of the expected covariance, means, and thresholds,  $V$  is the weight matrix used,  $W$  is the inverse of the full weight matrix, and  $U = VJ(J'VJ)^{-1}$ , then the asymptotic covariance matrix of the free parameters is

$$Acov(\theta) = U'WU$$

with  $U'$  indicating the transpose of  $U$ .

**Value**

A named list with components

**SE** The standard errors of the free parameters

**Cov** The full covariance matrix of the free parameters. The square root of the diagonal elements of Cov equals SE.

**Jac** The Jacobian computed to obtain the standard errors.

**References**

M. W. Browne. (1984). Asymptotically Distribution-Free Methods for the Analysis of Covariance Structures. *British Journal of Mathematical and Statistical Psychology*, 37, 62-83.

F. Yang-Wallentin, K. G. Jöreskog, & H. Luo. (2010). Confirmatory Factor Analysis of Ordinal Variables with Misspecified Models. *Structural Equation Modeling*, 17, 392-423.

---

 jointdata

---

*Joint Ordinal and continuous variables to be modeled together*


---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("jointdata")
```

**Format**

A data frame with 250 observations on the following variables.

z1 Continuous variable

z2 Ordinal variable with 2 levels (0, 1)

z3 Continuous variable

z4 Ordinal variable with 4 levels (0, 1, 2, 3)

z5 Ordinal variable with 3 levels (0, 1, 3)

**Details**

Data generated to test the joint ML algorithm thoroughly.

**Source**

Simulated.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(jointdata)
par(mfrow=c(2, 3))
h <- lapply(jointdata, hist)
par(mfrow=c(1, 1))

plot(z2 ~ z1, jointdata)
```

---

latentMultipleRegExample1

*Example data for multiple regression among latent variables*

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("latentMultipleRegExample1")
```

**Format**

A data frame with 200 observations on the following variables.

- X1 Factor 1 indicator
- X2 Factor 1 indicator
- X3 Factor 1 indicator
- X4 Factor 1 indicator
- X5 Factor 2 indicator
- X6 Factor 2 indicator
- X7 Factor 2 indicator
- X8 Factor 2 indicator
- X9 Factor 3 indicator

X10 Factor 3 indicator  
X11 Factor 3 indicator  
X12 Factor 3 indicator

**Details**

Factor 1 strongly predicts factor 3. Factor 2 weakly predicts factor 3.

**Source**

Simulated.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(latentMultipleRegExample1)  
round(cor(latentMultipleRegExample1), 2)
```

---

latentMultipleRegExample2

*Example data for multiple regression among latent variables*

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("latentMultipleRegExample2")
```

**Format**

A data frame with 200 observations on the following variables.

X1 Factor 1 indicator  
X2 Factor 1 indicator  
X3 Factor 1 indicator  
X4 Factor 1 indicator  
X5 Factor 2 indicator  
X6 Factor 2 indicator  
X7 Factor 2 indicator  
X8 Factor 2 indicator

X9 Factor 3 indicator  
X10 Factor 3 indicator  
X11 Factor 3 indicator  
X12 Factor 3 indicator

### Details

Factor 1 strongly predicts factor 3. Factor 2 weakly predicts factor 3. Very similar to [latentMultipleRegExample1](#).

### Source

Simulated.

### References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

### Examples

```
data(latentMultipleRegExample2)
round(cor(latentMultipleRegExample2), 2)
```

---

logm

*Matrix logarithm*

---

### Description

Matrix logarithm

### Usage

```
logm(x, tol = .Machine$double.eps)
```

### Arguments

x	matrix
tol	tolerance

---

LongitudinalOverdispersedCounts

*Longitudinal, Overdispersed Count Data*

---

### Description

Four-timepoint longitudinal data generated from an arbitrary Monte Carlo simulation, for 1000 simulees. The response variable is a discrete count variable. There are three time-invariant covariates. The data are available in both "wide" and "long" format.

### Usage

```
data("LongitudinalOverdispersedCounts")
```

### Format

The "long" format dataframe, `longData`, has 4000 rows and the following variables (columns):

1. `id`: Factor; simulee ID code.
2. `tiem`: Numeric; represents the time metric, wave of assessment.
3. `x1`: Numeric; time-invariant covariate.
4. `x2`: Numeric; time-invariant covariate.
5. `x3`: Numeric; time-invariant covariate.
6. `y`: Numeric; the response ("dependent") variable.

The "wide" format dataset, `wideData`, is a numeric 1000x12 matrix containing the following variables (columns):

1. `id`: Simulee ID code.
2. `x1`: Time-invariant covariate.
3. `x3`: Time-invariant covariate.
4. `x3`: Time-invariant covariate.
5. `y0`: Response at initial wave of assessment.
6. `y1`: Response at first follow-up.
7. `y2`: Response at second follow-up.
8. `y3`: Response at third follow-up.
9. `t0`: Time variable at initial wave of assessment (in this case, 0).
10. `t1`: Time variable at first follow-up (in this case, 1).
11. `t2`: Time variable at second follow-up (in this case, 2).
12. `t3`: Time variable at third follow-up (in this case, 3).

**Examples**

```

data(LongitudinalOverdispersedCounts)
head(wideData)
str(longData)
#Let's try ordinary least-squares (OLS) regression:
olsmod <- lm(y~tiem+x1+x2+x3, data=longData)
#We will see in the diagnostic plots that the residuals are poorly approximated by normality,
#and are heteroskedastic. We also know that the residuals are not independent of one another,
#because we have repeated-measures data:
plot(olsmod)
#In the summary, it looks like all of the regression coefficients are significantly different
#from zero, but we know that because the assumptions of OLS regression are violated that
#we should not trust its results:
summary(olsmod)

#Let's try a generalized linear model (GLM). We'll use the quasi-Poisson quasilielihood
#function to see how well the y variable is approximated by a Poisson distribution
#(conditional on time and covariates):
glm.mod <- glm(y~tiem+x1+x2+x3, data=longData, family="quasipoisson")
#The estimate of the dispersion parameter should be about 1.0 if the data are
#conditionally Poisson. We can see that it is actually greater than 2,
#indicating overdispersion:
summary(glm.mod)

```

---

multiData1

*Data for multiple regression*


---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("multiData1")
```

**Format**

A data frame with 500 observations on the following variables.

```

x1
x2
x3
x4
y

```

**Details**

x1-x4 are predictor variables, and y is the outcome.

**Source**

Simulated.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(multiData1)
summary(lm(y ~ ., data=multiData1))
#results can be replicated in OpenMx.
```

---

mxAlgebra

*Create MxAlgebra Object*


---

**Description**

This function creates a new [MxAlgebra](#) object.

**Usage**

```
mxAlgebra(expression, name = NA, dimnames = NA, ..., fixed = FALSE,
           joinKey=as.character(NA), joinModel=as.character(NA), verbose=0L)
```

**Arguments**

expression	An R expression of OpenMx-supported matrix operators and matrix functions.
name	An optional character string indicating the name of the object.
dimnames	list. The dimnames attribute for the algebra: a list of length 2 giving the row and column names respectively. An empty list is treated as NULL, and a list of length one as row names. The list can be named, and the list names will be used as names for the dimensions.
...	Not used. Forces argument 'fixed' to be specified by name.
fixed	If TRUE, this algebra will not be recomputed automatically when things it depends on change. <a href="#">mxComputeOnce</a> can be used to force it to recompute.
joinKey	The name of the column in current model's raw data that is used as a foreign key to match against the primary key in joinModel's raw data.
joinModel	The name of the model that this matrix joins against.
verbose	For values greater than zero, enable runtime diagnostics.

## Details

The `mxAlgebra` function is used to create algebraic expressions that operate on one or more `MxMatrix` objects. To evaluate an `MxAlgebra` object, it must be placed in an `MxModel` object, along with all referenced `MxMatrix` objects and the `mxFitFunctionAlgebra` function. The `mxFitFunctionAlgebra` function must reference by name the `MxAlgebra` object to be evaluated.

Note that, if the result for an `MxAlgebra` depends upon one or more "definition variables" (see `mxMatrix()`), then the value returned after the call to `mxRun()` will be computed using the values of those definition variables in the first (i.e., first before any automated sorting is done) row of the raw dataset.

The following operators and functions are supported in `mxAlgebra`:

### Operators

`solve()` Inversion

`t()` Transposition

`^` Elementwise powering

`%%` Kronecker powering

`+` Addition

`-` Subtraction

`%*%` Matrix Multiplication

`*` Elementwise product

`/` Elementwise division

`%x%` Kronecker product

`%&%` Quadratic product: pre- and post-multiply B by A and its transpose `t(A)`, i.e: `A %&% B == A %*% B %*% t(A)`

### Functions

`cov2cor` Convert covariance matrix to correlation matrix

`chol` Cholesky Decomposition

`cbind` Horizontal adhesion

`rbind` Vertical adhesion

`colSums` Matrix column sums as a column vector

`rowSums` Matrix row sums as a column vector

`det` Determinant

`tr` Trace

`sum` Sum

`mean` Arithmetic mean

`prod` Product

`max` Maximum

`min` Min



abs Absolute value  
sin Sine  
sinh Hyperbolic sine  
asin Arcsine  
asinh Inverse hyperbolic sine  
cos Cosine  
cosh Hyperbolic cosine  
acos Arccosine  
acosh Inverse hyperbolic cosine  
tan Tangent  
tanh Hyperbolic tangent  
atan Arctangent  
atanh Inverse hyperbolic tangent  
exp Exponent  
log Natural Logarithm  
mxRobustLog Robust natural logarithm  
sqrt Square root  
p2z *Standard*-normal quantile  
logp2z *Standard*-normal quantile from log probabilities  
lgamma Log-gamma function  
lgamma1p Compute  $\log(\Gamma(x+1))$  accurately for small  $x$   
eigenval Eigenvalues of a square matrix. Usage: eigenval(x); eigenvec(x); eigenval(x); eigenvec(x)  
rvectorize Vectorize by row  
cvectorize Vectorize by column  
vech Half-vectorization  
vechs Strict half-vectorization  
vech2full Inverse half-vectorization  
vechs2full Inverse strict half-vectorization  
vec2diag Create matrix from a diagonal vector (similar to [diag](#))  
diag2vec Extract diagonal from matrix (similar to [diag](#))  
expm Matrix Exponential  
logm Matrix Logarithm  
omxExponential Matrix Exponential  
omxMnor Multivariate Normal Integration  
omxAllInt All cells Multivariate Normal Integration  
omxNot Perform unary negation on a matrix

[omxAnd](#) Perform binary and on two matrices  
[omxOr](#) Perform binary or on two matrices  
[omxGreaterThan](#) Perform binary greater on two matrices  
[omxLessThan](#) Perform binary less than on two matrices  
[omxApproxEquals](#) Perform binary equals to (within a specified epsilon) on two matrices  
[omxSelectRows](#) Filter rows from a matrix  
[omxSelectCols](#) Filter columns from a matrix  
[omxSelectRowsAndCols](#) Filter rows and columns from a matrix  
[mxEvaluateOnGrid](#) Evaluate an algebra on an abscissa grid and collect column results

[mxRobustLog](#) is the same as `log` except that it returns `-745` instead of `-Inf` for an argument of 0. The value `-745` is less than `log(4.94066e-324)`, a good approximation of negative infinity because the log of any number represented as a double will be of smaller absolute magnitude.

There are also several multiargument functions usable in `MxAlgebras`, which apply themselves elementwise to the matrix provided as their first argument. These functions have slightly different usage from their R counterparts. Their result is always a matrix with the same dimensions as that provided for their first argument. Values must be provided for ALL arguments of these functions, in order. Provide zeroes as logical values of FALSE, and non-zero numerical values as logical values of TRUE. For most of these functions, OpenMx cycles over values of arguments other than the first, by column (i.e., in column-major order), to the length of the first argument. Notable exceptions are the `log`, `log.p`, and `lower.tail` arguments to probability-distribution-related functions, for which only the [1,1] element is used. It is recommended that all arguments after the first be either (1) scalars, or (2) matrices with the same dimensions as the first argument.

Function	Arguments	Notes
<code>besselI</code> & <code>besselK</code>	<code>x, nu, expon.scaled</code>	Note that OpenMx <i>does</i> cycle over the elements of <code>x</code>
<code>besselJ</code> & <code>besselY</code>	<code>x, nu</code>	
<code>dbeta</code>	<code>x, shape1, shape2, ncp, log</code>	The algorithm for the non-central beta distribution is u
<code>pbeta</code>	<code>q, shape1, shape2, ncp, lower.tail, log.p</code>	Values of <code>ncp</code> are handled as with <code>dbeta()</code> .
<code>dbinom</code>	<code>x, size, prob, log</code>	
<code>pbinom</code>	<code>q, size, prob, lower.tail, log.p</code>	
<code>dcauchy</code>	<code>x, location, scale, log</code>	
<code>pcauchy</code>	<code>q, location, scale, lower.tail, log.p</code>	
<code>dchisq</code>	<code>x, df, ncp, log</code>	The algorithm for the non-central chi-square distributi
<code>pchisq</code>	<code>q, df, ncp, lower.tail, log.p</code>	Values of <code>ncp</code> are handled as with <code>dchisq()</code> .
<code>omxDnbinom</code>	<code>x, size, prob, mu, log</code>	Exactly one of arguments <code>size</code> , <code>prob</code> , and <code>mu</code> should b
<code>omxPnbinom</code>	<code>q, size, prob, mu, lower.tail, log.p</code>	Arguments are handled as with <code>omxDnbinom()</code> .
<code>dpois</code>	<code>x, lambda, log</code>	
<code>ppois</code>	<code>q, lambda, lower.tail, log.p</code>	

## Value

Returns a new [MxAlgebra](#) object.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

[MxAlgebra](#) for the S4 class created by mxAlgebra. [mxFitFunctionAlgebra](#) for an objective function which takes an MxAlgebra or MxMatrix object as the function to be minimized. [MxMatrix](#) and [mxMatrix](#) for objects which may be entered in the expression argument and the function that creates them. More information about the OpenMx package may be found [here](#).

## Examples

```
A <- mxMatrix("Full", nrow = 3, ncol = 3, values=2, name = "A")

# Simple example: algebra B simply evaluates to the matrix A
B <- mxAlgebra(A, name = "B")

# Compute A + B
C <- mxAlgebra(A + B, name = "C")

# Compute sin(C)
D <- mxAlgebra(sin(C), name = "D")

# Make a model and evaluate the mxAlgebra object 'D'
A <- mxMatrix("Full", nrow = 3, ncol = 3, values=2, name = "A")
model <- mxModel(model="AlgebraExample", A, B, C, D )
fit <- mxRun(model)
mxEval(D, fit)

# Numbers in mxAlgebras are upgraded to 1x1 matrices
# Example of Kronecker powering (%%) and multiplication (%*)
A <- mxMatrix(type="Full", nrow=3, ncol=3, value=c(1:9), name="A")
m1 <- mxModel(model="kron", A, mxAlgebra(A %% 2, name="KroneckerPower"))
mxRun(m1)$KroneckerPower

# Running kron
# mxAlgebra 'KroneckerPower'
# $formula: A %% 2
# $result:
#      [,1] [,2] [,3]
# [1,]   1  16  49
# [2,]   4  25  64
# [3,]   9  36  81
```

---

MxAlgebra-class	<i>MxAlgebra Class</i>
-----------------	------------------------

---

### Description

MxAlgebra is an S4 class. An MxAlgebra object is a [named entity](#). New instances of this class can be created using the function [mxAlgebra](#).

### Details

The MxAlgebra class has the following slots:

name	-	The name of the object
formula	-	The R expression to be evaluated
result	-	a matrix with the computation result

The ‘name’ slot is the name of the MxAlgebra object. Use of MxAlgebra objects in the [mxConstraint](#) function or an objective function requires reference by name.

The ‘formula’ slot is an expression containing the expression to be evaluated. These objects are operated on or related to one another using one or more operations detailed in the [mxAlgebra](#) help file.

The ‘result’ slot is used to hold the results of computing the expression in the ‘formula’ slot. If the containing model has not been executed, then the ‘result’ slot will hold a 0 x 0 matrix. Otherwise the slot will store the computed value of the algebra using the final estimates of the free parameters.

Slots may be referenced with the \$ symbol. See the documentation for [Classes](#) and the examples in the [mxAlgebra](#) document for more information.

### References

The OpenMx User’s guide can be found at <http://openmx.ssri.psu.edu/documentation>.

### See Also

[mxAlgebra](#), [mxMatrix](#), [MxMatrix](#)

---

MxAlgebraFormula-class	<i>MxAlgebraFormula</i>
------------------------	-------------------------

---

### Description

This is an internal class for the formulas used in [mxAlgebra](#) calls.

---

mxAlgebraFromString    *Create MxAlgebra object from a string*

---

### Description

Create MxAlgebra object from a string

### Usage

```
mxAlgebraFromString(algString, name = NA, dimnames = NA, ...)
```

### Arguments

algString	the character string to convert into an R expression
name	An optional character string indicating the name of the object.
dimnames	list. The dimnames attribute for the algebra: a list of length 2 giving the row and column names respectively. An empty list is treated as NULL, and a list of length one as row names. The list can be named, and the list names will be used as names for the dimensions.
...	Not used. Forces any remaining arguments to be specified by name.

### See Also

[mxAlgebra](#)

### Examples

```
A <- mxMatrix(values = runif(25), nrow = 5, ncol = 5, name = 'A')
B <- mxMatrix(values = runif(25), nrow = 5, ncol = 5, name = 'B')
model <- mxModel(A, B, name = 'model',
  mxAlgebraFromString("A * (B + A)", name = 'test'))
model <- mxRun(model)
model[['test']]$result
A$values * (B$values + A$values)
```

---

mxAlgebraObjective    *DEPRECATED: Create MxAlgebraObjective Object*

---

**Description**

WARNING: Objective functions have been deprecated as of OpenMx 2.0.

Please use `MxFitFunctionAlgebra()` instead. As a temporary workaround, `MxAlgebraObjective` returns a list containing a NULL `MxExpectation` object and an `MxFitFunctionAlgebra` object.

All occurrences of

```
mxAlgebraObjective(algebra, numObs = NA, numStats = NA)
```

Should be changed to

```
mxFitFunctionAlgebra(algebra, numObs = NA, numStats = NA)
```

**Arguments**

<code>algebra</code>	A character string indicating the name of an <code>MxAlgebra</code> or <code>MxMatrix</code> object to use for optimization.
<code>numObs</code>	(optional) An adjustment to the total number of observations in the model.
<code>numStats</code>	(optional) An adjustment to the total number of observed statistics in the model.

**Details**

NOTE: THIS DESCRIPTION IS DEPRECATED. Please change to using `mxFitFunctionAlgebra` as shown in the example below.

Fit functions are functions for which free parameter values are chosen such that the value of the objective function is minimized. While the other fit functions in OpenMx require an expectation function for the model, the `mxAlgebraObjective` function uses the referenced `MxAlgebra` or `MxMatrix` object as the function to be minimized.

If a model's primary objective function is a `mxAlgebraObjective` objective function, then the referenced algebra in the objective function must return a 1 x 1 matrix (when using OpenMx's default optimizer). There is no restriction on the dimensions of an objective function that is not the primary, or 'topmost', objective function.

To evaluate an algebra objective function, place the following objects in a `MxModel` object: a `MxAlgebraObjective`, `MxAlgebra` and `MxMatrix` entities referenced by the `MxAlgebraObjective`, and optional `MxBounds` and `MxConstraint` entities. This model may then be evaluated using the `mxRun` function. The results of the optimization may be obtained using the `mxEval` function on the name of the `MxAlgebra`, after the model has been run.

**Value**

Returns a list containing a NULL `MxExpectation` object and an `MxFitFunctionAlgebra` object. `MxFitFunctionAlgebra` objects should be included with models with referenced `MxAlgebra` and `MxMatrix` objects.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

[mxAlgebra](#) to create an algebra suitable as a reference function to be minimized. More information about the OpenMx package may be found [here](#).

**Examples**

```
# Create and fit a very simple model that adds two numbers using mxFitFunctionAlgebra

library(OpenMx)

# Create a matrix 'A' with no free parameters
A <- mxMatrix('Full', nrow = 1, ncol = 1, values = 1, name = 'A')

# Create an algebra 'B', which defines the expression A + A
B <- mxAlgebra(A + A, name = 'B')

# Define the objective function for algebra 'B'
objective <- mxFitFunctionAlgebra('B')

# Place the algebra, its associated matrix and
# its objective function in a model
tmpModel <- mxModel(model="Addition", A, B, objective)

# Evaluate the algebra
tmpModelOut <- mxRun(tmpModel)

# View the results
tmpModelOut$output$minimum
```

---

mxAutoStart

*Automatically set starting values for an MxModel*


---

**Description**

Automatically set starting values for an MxModel

**Usage**

```
mxAutoStart(model, type = c("ULS", "DWLS"))
```

**Arguments**

model	The MxModel for which starting values are desired
type	The type of starting values to obtain, currently unweighted or diagonally weighted least squares, ULS or DWLS

## Details

This function automatically picks very good starting values for many models (RAM, LISREL, Normal), including multiple group versions of these. It works for models with algebras. Models of continuous, ordinal, and joint ordinal-continuous variables are also acceptable. It works for model with covariance or raw data. However, it does not currently work for models with definition variables, state space models, and item factor analysis models.

The method used to obtain new starting values is quite simple. The user's model is changed to an unweighted least squares (ULS) model. The ULS model is estimated and its final point estimates are returned as the new starting values. Optionally, diagonally weighted least squares (DWLS) can be used instead with the `type` argument.

Please note that ULS is sensitive to the scales of your variables. For example, if you have variables with means of 20 and variances of 0.001, then ULS will "weight" the means 20,000 times more than the variances and might result in zero variance estimates. Likewise if one variable has a variance of 20 and another has a variance of 0.001, the same problem may arise. To avoid this, make sure your variables are scaled accordingly. You could also use `type='DWLS'` to have the function use diagonally weighted least squares to obtain starting values. Of course, using diagonally weighted least squares will take much much longer and will usually not provide better starting values than unweighted least squares.

## Value

an MxModel with new free parameter values

## Examples

```
# Use the frontpage model with negative variances to show better
# starting values
library(OpenMx)
data(demoOneFactor)

latents = c("G") # the latent factor
manifests = names(demoOneFactor) # manifest variables to be modeled

m1 <- mxModel("One Factor", type = "RAM",
  manifestVars = manifests, latentVars = latents,
  mxPath(from = latents, to = manifests),
  mxPath(from = manifests, arrows = 2, values=-.2),
  mxPath(from = latents, arrows = 2, free = FALSE, values = 1.0),
  mxPath(from = "one", to = manifests),
  mxData(demoOneFactor, type = "raw")
)

# Starting values imply negative variances!
mxGetExpected(m1, 'covariance')

# Use mxAutoStart to get much better starting values
m1s <- mxAutoStart(m1)
mxGetExpected(m1s, 'covariance')
```



---

mxAvailableOptimizers *mxAvailableOptimizers*

---

**Description**

List the Optimizers available in this version, e.g. "SLSQP" "CSOLNP"

**Usage**

```
mxAvailableOptimizers()
```

**Details**

note for advanced users: Special-purpose optimizers like Newton-Raphson or EM are not included in this list.

**Value**

- list of valid Optimizer names

**See Also**

- [mxOption\(model, "Default optimizer"\)](#)

**Examples**

```
mxAvailableOptimizers()
```

---

MxBaseExpectation-class

*MxBaseExpectation*

---

**Description**

The virtual base class for all expectations. Expectations contain enough information to generate simulated data. This is an internal class and should not be used directly.

**See Also**

[mxExpectationNormal](#), [mxExpectationRAM](#), [mxExpectationLISREL](#), [mxExpectationStateSpace](#), [mxExpectationBA81](#)

---

MxBaseFitFunction-class

*MxBaseFitFunction*

---

### **Description**

The virtual base class for all fit functions. This is an internal class and should not be used directly.

### **See Also**

[mxFitFunctionAlgebra](#), [mxFitFunctionML](#), [mxFitFunctionMultigroup](#), [mxFitFunctionR](#), [mxFitFunctionWLS](#), [mxFitFunctionRow](#), [mxFitFunctionGREML](#)

---

MxBaseNamed-class

*MxBaseNamed*

---

### **Description**

This is an internal class and should not be used directly. It is the base class for named entities. Fit functions, expectations, and computes contain this class.

---

MxBaseObjectiveMetaData-class

*MxBaseObjectiveMetaData*

---

### **Description**

This is an internal class and should not be used directly. It is the virtual base class for all objective functions meta-data

mxBootstrap

*Repeatedly estimate model using resampling with replacement***Description**

Bootstrapping can help to assess the variability in parameter estimates. A new sample is drawn from current data by uniformly sampling the original data with replacement. Then the model is fit to these new data. This process is repeated many times. Quantiles of the estimates from all these replications can be used to assess the variability of parameters.

**Usage**

```
mxBootstrap(model, replications=200, ...,
            data=NULL, plan=NULL, verbose=0L,
            parallel=TRUE, only=as.integer(NA),
            OK=mxOption(model, "Status OK"), checkHess=FALSE)
```

**Arguments**

model	The MxModel to be run.
replications	The number of resampling replications. If available, replications from prior mxBootstrap invocations will be reused.
...	Not used. Forces remaining arguments to be specified by name.
data	A character vector of data or model names
plan	Deprecated
verbose	For levels greater than 0, enables runtime diagnostics
parallel	Whether to process the replications in parallel
only	When provided, only the given replication from a prior run of mxBootstrap will be performed. See details.
OK	The set of status code that are considered successful
checkHess	Whether to approximate the Hessian in each replication

**Details**

By default, all datasets in the given model are resampled independently. If resampling is desired from only some of the datasets then the models containing them can be listed in the 'data' parameter. The frequency column in the [mxData](#) object is used represent a resampled dataset. When resampling, the original row proportions, as given by the original frequency column, are respected.

When the model has a default compute plan and 'checkHess' is kept at FALSE then the Hessian will not be approximated or checked. On the other hand, 'checkHess' is TRUE then the Hessian will be approximated by finite differences. This procedure is of some value because it can be informative to check whether the Hessian is positive definite (see [mxComputeHessianQuality](#)). However, approximating the Hessian is often costly in terms of CPU time. For bootstrapping, the parameter estimates derived from the resampled data are typically of primary interest.

On occasion, replications will fail. Sometimes it can be helpful to exactly reproduce a failed replication to attempt to pinpoint the cause of failure. The ‘only’ option facilitates this kind of investigation. In normal operation, mxBootstrap uses the regular R random number generator to generate a seed for each replication. This seed is used to seed an internal pseudorandom number generator (currently the Mersenne Twister algorithm). These per-replication seeds are stored as part of the bootstrap output. When ‘only’ is specified, the associated stored seed is used to seed the internal random number generator so that identical weights can be regenerated.

‘mxBootstrap’ does not currently offer special support for nested or multilevel data. Rows are assumed model-wise independent.

### Value

The given model is returned with the compute plan modified to consist of mxComputeBootstrap. Results of the bootstrap replications are stored inside the compute plan. [mxSummary](#) can be used to obtain per-parameter quantiles and standard errors.

### See Also

[mxBootstrapEval](#), [mxComputeBootstrap](#), [mxSummary](#), [mxBootstrapStdizeRAMpaths](#), [as.statusCode](#)

### Examples

```
library(OpenMx)

data(multiData1)

manifests <- c("x1", "x2", "y")

biRegModelRaw <- mxModel(
  "Regression of y on x1 and x2",
  type="RAM",
  manifestVars=manifests,
  mxPath(from=c("x1", "x2"), to="y",
    arrows=1,
    free=TRUE, values=.2, labels=c("b1", "b2")),
  mxPath(from=manifests,
    arrows=2,
    free=TRUE, values=.8,
    labels=c("VarX1", "VarX2", "VarE")),
  mxPath(from="x1", to="x2",
    arrows=2,
    free=TRUE, values=.2,
    labels=c("CovX1X2")),
  mxPath(from="one", to=manifests,
    arrows=1, free=TRUE, values=.1,
    labels=c("MeanX1", "MeanX2", "MeanY")),
  mxData(observed=multiData1, type="raw"))

biRegModelRawOut <- mxRun(biRegModelRaw)

boot <- mxBootstrap(biRegModelRawOut, 10) # start with 10
```

```
summary(boot)

# Looks good, now do the rest
## Not run: boot <- mxBootstrap(boot)
summary(boot)

# examine replication 3
boot3 <- mxBootstrap(boot, only=3)

print(coef(boot3))
print(boot$compute$output$raw[3,names(coef(boot3))])
```

---

mxBootstrapEval

*Evaluate Values in a bootstrapped MxModel*


---

### Description

This function can be used to evaluate an arbitrary R expression that includes named entities from a [MxModel](#) object, or labels from a [MxMatrix](#) object.

### Usage

```
mxBootstrapEval(expression, model, defvar.row = 1, ...,
  bq=c(.25,.75), method=c('bcpci','quantile'))

mxBootstrapEvalByName(name, model, defvar.row = 1, ...,
  bq=c(.25,.75), method=c('bcpci','quantile'))

omxBootstrapEval(expression, model, defvar.row = 1L, ...)

omxBootstrapEvalCov(expression, model, defvar.row = 1L, ...)

omxBootstrapEvalByName(name, model, defvar.row=1L, ...)
```

### Arguments

expression	An arbitrary R expression.
name	The character name of an object to evaluate.
model	The model in which to evaluate the expression.
defvar.row	The row number for definition variables when compute=TRUE; defaults to 1. When compute=FALSE, values for definition variables are always taken from the first (i.e., first before any automated sorting is done) row of the raw data.
...	Not used. Forces remaining arguments to be specified by name.
bq	numeric. A vector of quantiles to be used to summarize bootstrap replication.
method	character. One of 'quantile' or 'bcpci'.

## Details

The argument 'expression' is an arbitrary R expression. Any named entities that are used within the R expression are translated into their current value from the model. Any labels from the matrices within the model are translated into their current value from the model. Finally the expression is evaluated and the result is returned. To enable debugging, the 'show' argument has been provided. The most common mistake when using this function is to include named entities in the model that are identical to R function names. For example, if a model contains a named entity named 'c', then the following mxEval call will return an error: `mxEval(c(A, B, C), model)`.

The `mxEvalByName` function is a wrapper around `mxEval` that takes a character instead of an R expression.

The default behavior is to use the 'bcpci' method, due to its superior theoretical properties.

## Value

`omxBootstrapEval` and `omxBootstrapEvalByName` return the raw matrix of `cvectorize`'d results. `omxBootstrapEvalCov` returns the covariance matrix of the `cvectorize`'d results. `mxBootstrapEval` and `mxBootstrapEvalByName` return the `cvectorize`'d results summarized by method at quantiles `bq`.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

[mxAlgebra](#) to create algebraic expressions inside your model and [mxModel](#) for the model object `mxEval` looks inside when evaluating. [mxBootstrap](#) to create bootstrap data.

## Examples

```
library(OpenMx)

testModel <- mxModel(
  model="testModel",
  mxData(data.frame(weight=1.0, value=1:10), "raw", weight = "weight"),
  mxMatrix("Full", nrow = 1, ncol = 1, values = 1, free=TRUE, name = "A"),
  mxAlgebra(data.weight * filteredDataRow, name = 'rowAlgebra'),
  mxAlgebra((sum(rowResults) - A)^2, name = 'reduceAlgebra'),
  mxFitFunctionRow('rowAlgebra', 'reduceAlgebra', 'value'))

testModel <- mxRun(testModel)
testBoot <- mxBootstrap(testModel)
summary(testBoot)

mxBootstrapEval(A^2, testBoot)
```

---

 mxBootstrapStdizeRAMpaths

*Bootstrap distribution of standardized RAM path coefficients*


---

### Description

Uses the bootstrap distribution of a RAM model's free parameters to produce a bootstrap distribution of standardized path coefficients. Model must have already been run through `mxBootstrap()`.

### Usage

```
mxBootstrapStdizeRAMpaths(model, bq=c(.25,.75),
  method=c('bcbci','quantile'), returnRaw=FALSE)
```

### Arguments

model	An MxModel that uses <a href="#">RAM expectation</a> and has already been run through <code>mxBootstrap()</code> .
bq	Quantiles corresponding to the lower and upper limits, respectively, of the bootstrap confidence interval.
method	Character string. One of 'bcbci' or 'quantile'.
returnRaw	Logical; should the function return the raw bootstrapping results? Defaults to FALSE, in which case a dataframe summarizing the results is returned.

### Details

In effect, what `mxBootstrapStdizeRAMpaths()` does is use the point estimates from each bootstrap replication to produce `mxStandardizeRAMpaths()` output for each replication. The output of `mxStandardizeRAMpaths()` has one entry for each nonzero path coefficient. Therefore, it is possible (though unlikely) that the number of nonzero paths, or which elements of the A and S RAM matrices are nonzero, may vary among bootstrap replications. Such an occurrence defies simple summary of the standardized paths' bootstrapping results. In this case, a raw list of bootstrapping results is returned, with a warning, if `returnRaw=TRUE`, or an error is throw if `returnRaw=FALSE`.

`mxBootstrapStdizeRAMpaths()` ignores any submodels of `model`. That is, it must be able to find, in the MxModel it is provided, a [RAM expectation](#) and an `MxComputeBootstrap` object. It can be run on submodels directly,

### Value

Under extraordinary circumstances described above, `mxBootstrapStdizeRAMpaths()` may return a list object. In ordinary circumstances, if `returnRaw=FALSE` (default), it returns a dataframe containing, *inter alia*, the standardized path coefficients as estimated from the real data, their bootstrap SEs, and the lower and upper limits of a bootstrap confidence interval. If instead `returnRaw=TRUE`, `mxBootstrapStdizeRAMpaths()` returns a matrix containing the raw bootstrap results; this matrix has one column per nonzero path coefficient, and one row for each successfully converged bootstrap replication.

**See Also**

[mxBootstrap\(\)](#), [mxStandardizeRAMpaths\(\)](#), [mxBootstrapEval](#), [mxSummary](#)

**Examples**

```
require(OpenMx)
data(myFADataRaw)
myFADataRaw <- myFADataRaw[,c("x1", "x2", "x3", "x4", "x5", "x6")]
dataRaw <- mxData( observed=myFADataRaw, type="raw" )
resVars <- mxPath( from=c("x1", "x2", "x3", "x4", "x5", "x6"), arrows=2,
                  free=TRUE, values=c(1,1,1,1,1,1),
                  labels=c("e1", "e2", "e3", "e4", "e5", "e6") )
latVar <- mxPath( from="F1", arrows=2,
                  free=TRUE, values=1, labels = "varF1" )
facLoads <- mxPath( from="F1", to=c("x1", "x2", "x3", "x4", "x5", "x6"), arrows=1,
                  free=c(FALSE, TRUE, TRUE, TRUE, TRUE, TRUE), values=c(1,1,1,1,1,1),
                  labels =c("l1", "l2", "l3", "l4", "l5", "l6") )
means <- mxPath( from="one", to=c("x1", "x2", "x3", "x4", "x5", "x6", "F1"), arrows=1,
                 free=c(TRUE, TRUE, TRUE, TRUE, TRUE, TRUE, FALSE),
                 values=c(1,1,1,1,1,1,0),
                 labels =c("meanx1", "meanx2", "meanx3",
                           "meanx4", "meanx5", "meanx6", NA) )
oneFactorModel <- mxModel("Common Factor Model Path Specification", type="RAM",
                          manifestVars=c("x1", "x2", "x3", "x4", "x5", "x6"), latentVars="F1",
                          dataRaw, resVars, latVar, facLoads, means)
oneFactorFit <- mxRun(oneFactorModel)
set.seed(170505)

## Not run: oneFactorBoot <- mxBootstrap(oneFactorFit)
## mxBootstrapStdizeRAMpaths(oneFactorBoot)
## End(Not run)
```

---

mxBounds

*Create MxBounds Object*

---

**Description**

This function creates a new [MxBounds](#) object.

**Usage**

```
mxBounds(parameters, min = NA, max = NA)
```

**Arguments**

parameters	A character vector indicating the names of the parameters on which to apply bounds.
min	A numeric value for the lower bound. NA means use default value.
max	A numeric value for the upper bound. NA means use default value.



**Details**

Creates a set of boundaries or limits for a parameter or set of parameters. Parameters may be any free parameter or parameters from an [MxMatrix](#) object. Parameters may be referenced either by name or by referring to their position in the 'spec' matrix of an [MxMatrix](#) object.

Minima and maxima may be specified as scalar numeric values.

**Value**

Returns a new [MxBounds](#) object. If used as an argument in an [MxModel](#) object, the parameters referenced in the 'parameters' argument must also be included prior to optimization.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

[MxBounds](#) for the S4 class created by `mxBounds`. [MxMatrix](#) and [mxMatrix](#) for free parameter specification. More information about the OpenMx package may be found [here](#).

**Examples**

```
#Create lower and upper bounds for parameters 'A' and 'B'
bounds <- mxBounds(c('A', 'B'), 3, 5)

#Create a lower bound of zero for a set of variance parameters
varianceBounds <- mxBounds(c('Var1', 'Var2', 'Var3'), 0)
```

---

MxBounds-class

*MxBounds Class*


---

**Description**

MxBounds is an S4 class. New instances of this class can be created using the function [mxBounds](#).

**Details**

The MxBounds class has the following slots:

min	-	The lower bound
max	-	The upper bound
parameters	-	The vector of parameter names

The 'min' and 'max' slots hold scalar numeric values for the lower and upper bounds on the list of parameters, respectively.

Parameters may be any free parameter or parameters from an [MxMatrix](#) object. Parameters may be referenced either by name or by referring to their position in the 'spec' matrix of an [MxMatrix](#) object. To affect an estimation or optimization, an [MxBounds](#) object must be included in an [MxModel](#) object with all referenced [MxAlgebra](#) and [MxMatrix](#) objects.

Slots may be referenced with the \$ symbol. See the documentation for [Classes](#) and the examples in the [mxBounds](#) document for more information.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

[mxBounds](#) for the function that creates [MxBounds](#) objects. [MxMatrix](#) and [mxMatrix](#) for free parameter specification. More information about the OpenMx package may be found [here](#).

---

MxCharOrList-class     *A character, list or NULL*

---

## Description

A character, list or NULL

---

MxCharOrLogical-class     *A character or logical*

---

## Description

A character or logical

---

MxCharOrNumber-class     *A character or integer*

---

## Description

A character or integer

---

mxCheckIdentification *Check that a model is locally identified*

---

### Description

Use the dimension of the null space of the Jacobian to determine whether or not a model is identified local to its current parameter values. The output is a list of the the identification status, the Jacobian, and which parameters are not identified.

### Usage

```
mxCheckIdentification(model, details=TRUE)
```

### Arguments

model	A MxModel object or list of MxModel objects.
details	logical.

### Details

The mxCheckIdentification function is used to check that a model is identified. That is, the function will tell you if the model has a unique solution in parameter space. The function is most useful when applied to either (a) a model that has been run and had some NA standard errors, or (b) a model that has not been run but has reasonable starting values. In the former situation, mxCheckIdentification is used as a diagnostic after a problem was indicated. In the latter situation, mxCheckIdentification is used as a sanity check.

The method uses the Jacobian of the model expected means and the unique elements of the expected covariance matrix with respect to the free parameters. It is the first derivative of the mapping between the free parameters and the sufficient statistics for the Normal distribution. The method does not depend on data, but does depend on the current values of the free parameters. Thus, it only provides local identification, not global identification. Because the method does not depend on data, the model still could be empirically unidentified due to missing data.

The Jacobian is evaluated numerically and generally takes a few seconds, but much less than a minute.

The identification may not be accurate for model where definition variables are used. Currently, only the first row of the definition variable is evaluated.

When TRUE, the 'details' argument provides the names of the non-identified parameters. Otherwise, only the status and Jacobian are returned.

### Value

A named list with components

**status** logical. TRUE if the model is locally identified; otherwise FALSE.

**jacobian** matrix. The numerically evaluated Jacobian.

**non\_identified\_parameters** vector. The free parameter names that are not identified

## References

- Bekker, P.A., Merckens, A., Wansbeek, T.J. (1994). Identification, Equivalent Models and Computer Algebra. Academic Press: Orlando, FL.
- Bollen, K. A. & Bauldry, S. (2010). Model Identification and Computer Algebra. Sociological Methods & Research, 39, p. 127-156.

## See Also

[mxModel](#)

## Examples

```
require(OpenMx)

data(demoOneFactor)
manifests <- names(demoOneFactor)
latents <- "G1"
model2 <- mxModel(model="One Factor", type="RAM",
  manifestVars = manifests,
  latentVars = latents,
  mxPath(from = latents[1], to=manifests[1:5]),
  mxPath(from = manifests, arrows = 2, lbound=1e-6),
  mxPath(from = latents, arrows = 2, free = FALSE, values = 1.0),
  mxData(cov(demoOneFactor), type = "cov", numObs=500)
)
fit2 <- mxRun(model2)

id2 <- mxCheckIdentification(fit2)
id2$status
# The model is locally identified

# Build a model from the solution of the previous one
# but now the factor variance is also free
model2n <- mxModel(fit2, name="Non Identified Two Factor",
  mxPath(from=latents[1], arrows=2, free=TRUE, values=1)
)

mid2 <- mxCheckIdentification(model2n)
mid2$non_identified_parameters
# The factor loadings and factor variance
# are not identified.
```

**Description**

This function creates a new [MxCI](#) object, which are used to estimate likelihood-based confidence intervals.

**Usage**

```
mxCI(reference, interval = 0.95, type=c("both", "lower", "upper"), ..., boundAdj=TRUE)
```

**Arguments**

reference	A character vector of free parameters, mxMatrices, mxMatrix elements and mx-Algebras on which confidence intervals are to be estimated, listed by name.
interval	A scalar numeric value indicating the confidence interval to be estimated. Must be between 0 and 1. Defaults to 0.95.
type	A character string indicating whether the upper, lower or both confidence limits are returned. Defaults to "both".
...	Not used. Forces remaining arguments to be specified by name.
boundAdj	Whether to correct the likelihood-based confidence intervals for a lower or upper bound.

**Details**

The `mxCI` function creates [MxCI](#) objects, which can be used as arguments in [MxModel](#) objects. When models containing [MxCI](#) objects are optimized using `mxRun` with the 'intervals' argument set to TRUE, likelihood-based confidence intervals are returned. The likelihood-based confidence intervals calculated by [MxCI](#) objects are symmetric with respect to the change in likelihood in either direction, and are not necessarily symmetric around the parameter estimate. Estimation of confidence intervals requires both that an [MxCI](#) object be included in the model and that the 'intervals' argument of the `mxRun` function is set to TRUE. When estimated, confidence intervals can be accessed in the model output at `$output$confidenceIntervals` or by using `summary` on a fitted [MxModel](#) object.

A typical use case is when a model includes non-linear constraints, and hence, standard errors are not available. In all cases, a two-sided hypothesis test is assumed. Therefore, the upper bound will exclude 2.5% (for `interval=0.95`) even though only one bound is requested. To obtain a one-sided CI for a one-sided hypothesis test, `interval=0.90` will obtain a 95% confidence interval.

When a confidence interval is requested for a free parameter (not an algebra) constrained by a lower bound or an upper bound (but not both) and `boundAdj=TRUE` then the Wu & Neale (2012) correction is used. This improves the accuracy of the confidence interval when the parameter is estimated close to the bound. For example, this correction will be activated when a variance with a lower bound of  $10^{-6}$  and no upper bound that is estimated close to the bound. The sample size, or more precisely effective sample size for that particular parameter, will determine how close the variance needs to be to the bound at  $10^{-6}$  to activate the correction.

The likelihood-based confidence intervals returned using [MxCI](#) are obtained by increasing or decreasing the value of each parameter until the -2 log likelihood of the model increases by an amount corresponding to the requested interval. The confidence limit specified by the 'interval' argument is transformed into a corresponding difference in the model -2 log likelihood based on the likelihood

ratio test. Thus, a requested confidence interval for a parameter will first determine the corresponding quantile from the chi-squared distribution with one degree of freedom (a value of 3.841459 when a 95 percent confidence interval is requested). That quantile will be populated into either the ‘lowerdelta’ slot, the ‘upperdelta’ slot, or both in the output **MxCI** object.

Estimation of likelihood-based confidence intervals begins after optimization has been completed, with each parameter moved in the direction(s) specified in the ‘type’ argument until the specified increase in -2 log likelihood is reached. All other free parameters are left free for this stage of optimization. This process repeats until all confidence intervals have been calculated. The calculation of likelihood-based confidence intervals can be computationally intensive, and may add a significant amount of time to model estimation when many confidence intervals are requested.

Multiple parameters, **MxMatrices** and **MxAlgebras** may be listed in the ‘reference’ argument. Individual elements of **MxMatrices** and **MxAlgebras** may be listed as well, using the syntax “matrix[row,col]” (see **Extract** for more information). Only scalar numeric values for the ‘interval’ argument are supported. Users requesting different confidence ranges for different parameters must use separate **mxCI** statements. **MxModel** objects can hold multiple **MxCI** objects, but only one confidence interval may be requested per named-entity.

Confidence interval estimation may result in model non-convergence at the confidence limit. Separate optimizer messages may be passed for each confidence limit. This has no impact on the parameter estimates themselves, but may indicate a problem with the referenced confidence limit. Model non-convergence for a particular confidence limit may indicate parameter interdependence or the influence of a parameter boundary.

These error messages and their meanings are listed in the help for **mxSummary**

The validity of a confidence limit can be checked by running a model with the appropriate parameter fixed at the confidence limit in question. If the confidence limit is valid, the -2 log likelihoods of these two models should differ by the specified chi-squared criterion (as set using the ‘lowerdelta’ or ‘upperdelta’ slots in the **MxCI** object (you can choose which of these to set via the type parameter of **mxCI**).

## Value

Returns a new **MxCI** object. If used as an argument in an **MxModel** object, the parameters, **MxMatrices** and **MxAlgebras** listed in the ‘reference’ argument must also be included prior to optimization.

## References

The OpenMx User’s guide can be found at <http://openmx.ssri.psu.edu/documentation>. Additional support for **mxCI()** can be found on the OpenMx wiki at <http://openmx.ssri.psu.edu/wiki>.

Neale, M. C. & Miller M. B. (1997). The use of likelihood based confidence intervals in genetic models. *Behavior Genetics*, 27(2), 113-120.

Pek, J. & Wu, H. (2015). Profile likelihood-based confidence intervals and regions for structural equation models. *Psychometrika*, 80(4), 1123-1145.

Wu, H. & Neale, M. C. (2012). Adjusted confidence intervals for a bounded parameter. *Behavior genetics*, 42(6), 886-898.

**See Also**

**MxCI** for the S4 class created by mxCI. **mxComputeConfidenceInterval** is the internal compute plan that implements the algorithm. **MxMatrix** and **mxMatrix** for free parameter specification. More information about the OpenMx package may be found [here](#).

**Examples**

```

library(OpenMx)

# generate data
covariance <- matrix(c(1.0, 0.5, 0.5, 1.0),
  nrow=2,
  dimnames=list(c("a", "b"), c("a", "b")))

data <- mxData(covariance, "cov", numObs=100)

# create an expected covariance matrix
expect <- mxMatrix("Symm", 2, 2,
  free=TRUE,
  values=c(1, .5, 1),
  labels=c("var1", "cov12", "var2"),
  name="expectedCov")

# request 95 percent confidence intervals
ci <- mxCI(c("var1", "cov12", "var2"))

# specify the model
model <- mxModel(model="Confidence Interval Example",
  data, expect, ci,
  mxExpectationNormal("expectedCov", dimnames=c("a", "b")),
  mxFitFunctionML())

# run the model
results <- mxRun(model, intervals=TRUE)

# view confidence intervals
print(summary(results)$CI)

# view all results
summary(results)

# remove a specific mxCI from a model
model <- mxModel(model, remove=TRUE, model$intervals[['cov12']])
model$intervals

# remove all mxCI from a model
model <- mxModel(model, remove=TRUE, model$intervals)
model$intervals

```

---

MxCI-class

*MxCI Class*


---

### Description

MxCI is an S4 class. An MxCI object is a [named entity](#). New instances of this class can be created using the function `mxCI`. MxCI objects may be used as arguments in the `mxModel` function.

### Details

The MxCI class has the following slots:

- reference - The name of the object
- lowerdelta - Either a matrix or a data frame
- upperdelta - A vector for means, or NA if missing

The reference slot contains a character vector of named free parameters, [MxMatrices](#) and [MxAlgebras](#) on which confidence intervals are desired. Individual elements of [MxMatrices](#) and [MxAlgebras](#) may be listed as well, using the syntax “matrix[row,col]” (see [Extract](#) for more information).

The lowerdelta and upperdelta slots give the changes in likelihoods used to define the confidence interval. The upper bound of the likelihood-based confidence interval is estimated by increasing the parameter estimate, leaving all other parameters free, until the model -2 log likelihood increased by ‘upperdelta’. The lower bound of the confidence interval is estimated by decreasing the parameter estimate, leaving all other parameters free, until the model -2 log likelihood increased by ‘lowerdata’.

Likelihood-based confidence intervals may be specified by including one or more MxCI objects in an [MxModel](#) object. Estimation of confidence intervals requires model optimization using the `mxRun` function with the ‘intervals’ argument set to TRUE. The calculation of likelihood-based confidence intervals can be computationally intensive, and may add a significant amount of time to model estimation when many confidence intervals are requested.

### References

The OpenMx User’s guide can be found at <http://openmx.ssri.psu.edu/documentation>.

### See Also

`mxCI` for creating MxCI objects. More information about the OpenMx package may be found [here](#).



mxCompare

*Likelihood ratio test***Description**

Compare the fit of a model or set of models to a reference model or set of reference models.

**Usage**

```
mxCompare(base, comparison, ..., all = FALSE,
          boot=FALSE, replications=400, previousRun=NULL, checkHess=FALSE)
mxCompareMatrix(models,
                diag=c('minus2LL', 'ep', 'df', 'AIC'),
                stat=c('p', 'diffLL', 'diffdf'), ...,
                boot=FALSE, replications=400, previousRun=NULL,
                checkHess=FALSE, wholeTable=FALSE)
```

**Arguments**

base	A MxModel object or list of MxModel objects.
comparison	A MxModel object or list of MxModel objects.
models	A MxModel object or list of MxModel objects.
diag	statistic used for diagonal entries
stat	statistic used for off-diagonal entries
...	Not used.
all	A boolean value on whether to compare all bases with all comparisons. Defaults to FALSE.
boot	Whether to use the bootstrap distribution to compute the p-value.
replications	How many replications to use to approximate the bootstrap distribution.
previousRun	Results to re-use from a previous bootstrap.
checkHess	Whether to approximate the Hessian in each replication
wholeTable	Return the whole table instead of a matrix shaped summary

**Details**

The mxCompare function is used to compare the fit of one or more [MxMatrix](#) objects with output to one or more comparison models. mxCompareMatrix compares all the models provided against each other. Fit statistics for the comparison model or models are subtracted from the fit statistics for the base model or models. All models included in the ‘base’ argument are also listed without comparison (compared to a <NA> model) to present their raw fit statistics.

Model comparisons are made by subtracting the fit of the comparison model from the fit of a base model. To make sure that the differences between models are positive and yield p-values for likelihood ratio tests, the model or models listed in the ‘base’ argument should be more saturated (i.e.,

more estimated parameters and fewer degrees of freedom) than models listed in the 'comparison' argument. For `mxCompareMatrix` only the comparisons that make sense will be included. If a comparison is made where the comparison model has a higher minus 2 log likelihood (-2LL) than the base model, then the difference in their -2LLs will be negative. P-values for likelihood ratio tests will not be reported when either the -2LL or degrees of freedom for the comparison are negative.

When multiple models are included in both the 'base' and 'comparison' arguments, then comparisons are made between the two lists of models based on the value of the 'all' argument. If 'all' is set to `FALSE` (default), then the first model in the 'base' list is compared to the first model in the 'comparison' list, second with second, and so on. If there are an unequal number of 'base' and 'comparison' models, then the shorter list of models is repeated to match the length of the longer list. For example, comparing base models 'B1' and 'B2' with comparison models 'C1', 'C2' and 'C3' will yield three comparisons: 'B1' with 'C1', 'B2' with 'C2', and 'B1' with 'C3'. Each of those comparisons are prefaced by a comparison between the base model and a missing comparison model to present the fit of the base model.

If 'all' is set to `TRUE`, all possible comparisons between base and comparison models are made, and one entry is made for each base model. All comparisons involving the first model in 'base' are made first, followed by all comparisons with the second 'base' model, and so on. When there are multiple models in either the 'base' or 'comparison' arguments but not both, then the 'all' argument does not affect the set of comparisons made.

The following columns appear in the output:

**base** Name of the base model.

**comparison** Name of the comparison model. Is `<NA>` for the first

**ep** Estimated parameters of the comparison model.

**minus2LL** Minus 2\*log-likelihood of the comparison model. If the comparison model is `<NA>`, then the minus 2\*log-likelihood of the base model is given.

**df** Degrees in freedom of the comparison model. If the comparison model is `<NA>`, then the degrees of freedom of the base model is given.

**AIC** Akaike's Information Criterion for the comparison model. If the comparison model is `<NA>`, then the AIC of the base model is given.

**diffLL** Difference in minus 2\*log-likelihoods of the base and comparison models. Will be positive when base model -2LL is higher than comparison model -2LL.

**diffdf** Difference in degrees of freedoms of the base and comparison models. Will be positive when base model DF is lower than comparison model DF (base model estimated parameters is higher than comparison model estimated parameters)

**p** P-value for likelihood ratio test based on `diffLL` and `diffdf` values.

The `mxCompare` function will give a p-value for any comparison in which both 'diffLL' and 'diffdf' are non-negative. However, this p-value is based on the assumptions of the likelihood ratio test, specifically that the two models being compared are nested. The likelihood ratio test and associated p-values are not valid when the comparison model is not nested in the referenced base model. For a more accurate p-value, the empirical bootstrap distribution can be computed ('boot=`TRUE`'). However, 'replications' must be set high enough for an accurate approximation. The Monte Carlo SE of a proportion for B replications is  $\sqrt{p*(1-p)/B}$ , but this will be zero if p is zero, which is nonsense. Note that a parametric-bootstrap p-value of zero must be interpreted as  $p < 1/B$ , which, depending on B and the desired Type I error rate, may not be "statistically significant."

When ‘boot=TRUE’, the model has a default compute plan, and ‘checkHess’ is kept at FALSE then the Hessian will not be approximated or checked. On the other hand, ‘checkHess’ is TRUE then the Hessian will be approximated by finite differences. This procedure is of some value because it can be informative to check whether the Hessian is positive definite (see [mxComputeHessianQuality](#)). However, approximating the Hessian is often costly in terms of CPU time. For bootstrapping, the parameter estimates derived from the resampled data are typically of primary interest.

Use options(‘digits’ = N) to set the minimum number of significant digits to be printed in values. The mxCompare function does not directly accept a digits argument, and depends on the value of the ‘digits’ option.

### See Also

[mxPowerSearch](#); [mxModel](#); [options](#) (use options(‘mxOptions’) to see all the OpenMx-specific options)

### Examples

```
data(demoOneFactor)
manifests <- names(demoOneFactor)
latents <- c("G1")
model1 <- mxModel(model="One Factor", type="RAM",
  manifestVars = manifests,
  latentVars = latents,
  mxPath(from = latents, to=manifests),
  mxPath(from = manifests, arrows = 2),
  mxPath(from = latents, arrows = 2, free = FALSE, values = 1.0),
  mxData(cov(demoOneFactor), type = "cov", numObs = 500)
)

fit1 <- mxRun(model1)

latents <- c("G1", "G2")
model2 <- mxModel(model="Two Factor", type="RAM",
  manifestVars = manifests,
  latentVars = latents,
  mxPath(from = latents[1], to=manifests[1:3]),
  mxPath(from = latents[2], to=manifests[4:5]),
  mxPath(from = manifests, arrows = 2),
  mxPath(from = latents, arrows = 2, free = FALSE, values = 1.0),
  mxData(cov(demoOneFactor), type = "cov", numObs=500)
)

fit2 <- mxRun(model2)

mxCompare(fit1, fit2)

# vary precision of the output
oldPrecision = as.numeric(options('digits'))
options('digits' = 1)
mxCompare(fit1, fit2)
options('digits' = oldPrecision)
```

---

MxCompute-class	<i>MxCompute</i>
-----------------	------------------

---

**Description**

This is an internal class and should not be used directly.

---

mxComputeBootstrap	<i>Repeatedly estimate model using resampling with replacement</i>
--------------------	--

---

**Description**

This is a low-level compute plan object to perform resampling with replacement.

**Usage**

```
mxComputeBootstrap(data, plan, replications=200, ...,
                   verbose=0L, parallel=TRUE, freeSet=NA_character_,
                   OK=c("OK", "OK/green"), only=NA_integer_)
```

**Arguments**

data	A vector of dataset or model names.
plan	The compute plan used to optimize the model for each data set.
replications	The number of resampling replications. If available, replications from prior mxBootstrap invocations will be reused.
...	Not used. Forces remaining arguments to be specified by name.
verbose	For levels greater than 0, enables runtime diagnostics
parallel	Whether to process the replications in parallel
freeSet	names of matrices containing free variables
OK	The set of status code that are considered successful
only	When provided, only the given replication from a prior run of mxBootstrap will be performed. See details.

**Details**

The ‘only’ option facilitates investigation of a single replication attempt.

**Value**

Output is stored in the compute object's output slot. Specifically, `model$compute$output$raw` contains a data frame with parameters in columns and replications in rows. In addition to parameters, the seed, fit, and statusCode of the replication is also included.

When 'only' is set to a particular replications, the weight vectors (one per dataset) are also returned in the compute object's output slot. `model$compute$output$weight` is a character vector (by dataset name) of numeric vectors (the weights). These weights can be used to recreate a model identical to the model used in the given replication.

**See Also**

[mxBootstrap, as.statusCode](#)

---

`mxComputeCheckpoint`    *Log parameters and state to disk or memory*

---

**Description**

Captures the current state of the backend. When path is set, the state is written to disk in a single row. When toReturn is set, the state is recorded in memory and returned after `mxRun`.

**Usage**

```
mxComputeCheckpoint(what=NULL, ..., path=NULL, append=FALSE, header=TRUE, toReturn=FALSE,
  parameters=TRUE, loopIndices=TRUE,
  fit=TRUE, counters=TRUE, status=TRUE)
```

**Arguments**

<code>what</code>	a character vector of algebra names to include in each checkpoint
<code>...</code>	Not used. Forces remaining arguments to be specified by name.
<code>path</code>	a character vector of where to write the checkpoint file
<code>append</code>	if FALSE, truncates the checkpoint file upon open. If TRUE, existing data is preserved and checkpoints are appended.
<code>header</code>	whether to write the header that describes the content of each column
<code>toReturn</code>	logical. Whether to store the checkpoint in memory and return it after the model is run
<code>parameters</code>	logical. Whether to include the parameter vector
<code>loopIndices</code>	logical. Whether to include the loop indices
<code>fit</code>	logical. Whether to include the fit value
<code>counters</code>	logical. Whether to include counters (number of evaluations and iterations)
<code>status</code>	logical. Whether to include the status code

---

 mxComputeConfidenceInterval

*Find likelihood-based confidence intervals*


---

### Description

There are various equivalent ways to pose the optimization problems required to estimate confidence intervals. Most accurate solutions are achieved when the problem is posed using non-linear constraints. However, the available optimizers (CSOLNP, SLSQP, and NPSOL) often have difficulty with non-linear constraints.

### Usage

```
mxComputeConfidenceInterval(plan, ..., freeSet = NA_character_,
  verbose = 0L, engine = NULL, fitfunction = "fitfunction",
  tolerance = NA_real_, constraintType = "none")
```

### Arguments

plan	compute plan to optimize the model
...	Not used. Forces remaining arguments to be specified by name.
freeSet	names of matrices containing free variables
verbose	level of debugging output
engine	deprecated
fitfunction	the name of the deviance function
tolerance	deprecated
constraintType	one of c('ineq', 'none')

### References

- Neale, M. C. & Miller M. B. (1997). The use of likelihood based confidence intervals in genetic models. *Behavior Genetics*, 27(2), 113-120.
- Pek, J. & Wu, H. (2015). Profile likelihood-based confidence intervals and regions for structural equation models. *Psychometrika*, 80(4), 1123-1145.
- Wu, H. & Neale, M. C. (2012). Adjusted confidence intervals for a bounded parameter. *Behavior genetics*, 42(6), 886-898.

---

mxComputeDefault	<i>Default compute plan</i>
------------------	-----------------------------

---

**Description**

The default compute plan is approximately as follows: `mxComputeSequence(list(mxComputeGradientDescent(), mxComp`

**Usage**

```
mxComputeDefault(freeSet = NA_character_)
```

**Arguments**

freeSet	names of matrices containing free variables
---------	---

---

mxComputeEM	<i>Fit a model using DLR's (1977) Expectation-Maximization (EM) algorithm</i>
-------------	---

---

**Description**

The EM algorithm constitutes the following steps: Start with an initial parameter vector. Predict the missing data to form a completed data model. Optimize the completed data model to obtain a new parameter vector. Repeat these steps until convergence criteria are met.

**Usage**

```
mxComputeEM(expectation = NULL, predict = NA_character_, mstep,
  observedFit = "fitfunction", ..., maxIter = 500L, tolerance = 1e-09,
  verbose = 0L, freeSet = NA_character_, accel = "varadhan2008",
  information = NA_character_, infoArgs = list(), estep = NULL)
```

**Arguments**

expectation	a vector of expectation names (DEPRECATED)
predict	what to predict from the observed data (DEPRECATED)
mstep	a compute plan to optimize the completed data model
observedFit	the name of the observed data fit function (defaults to "fitfunction")
...	Not used. Forces remaining arguments to be specified by name.
maxIter	maximum number of iterations
tolerance	optimization is considered converged when the maximum relative change in fit is less than tolerance
verbose	level of diagnostic output

freeSet	names of matrices containing free variables
accel	name of acceleration method ("varadhan2008" or "ramsay1975")
information	name of information matrix approximation method
infoArgs	arguments to control the information matrix method
estep	a compute plan to perform the expectation step

### Details

This compute plan does not work with any and all expectations. It requires a special kind of expectation that can predict its missing data to create a completed data model.

The EM algorithm does not produce a parameter covariance matrix for standard errors. The Oakes (1999) direct method and S-EM, an implementation of Meng & Rubin (1991), are included.

Ramsay (1975) was recommended in Bock, Gibbons, & Muraki (1988).

### References

- Bock, R. D., Gibbons, R., & Muraki, E. (1988). Full-information item factor analysis. *Applied Psychological Measurement*, 6(4), 431-444.
- Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society. Series B (Methodological)*, 1-38.
- Meng, X.-L. & Rubin, D. B. (1991). Using EM to obtain asymptotic variance-covariance matrices: The SEM algorithm. *Journal of the American Statistical Association*, 86 (416), 899-909.
- Oakes, D. (1999). Direct calculation of the information matrix via the EM algorithm. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 61(2), 479-482.
- Ramsay, J. O. (1975). Solving implicit equations in psychometric data analysis. *Psychometrika*, 40 (3), 337-360.
- Varadhan, R. & Roland, C. (2008). Simple and globally convergent methods for accelerating the convergence of any EM algorithm. *Scandinavian Journal of Statistics*, 35, 335-353.

---

mxComputeGenerateData *Generate data*

---

### Description

Generate data specified by the model expectations.

### Usage

```
mxComputeGenerateData(expectation = "expectation")
```

### Arguments

expectation a character vector of expectations to generate data for



---

 mxComputeGradientDescent

*Optimize parameters using a gradient descent optimizer*


---

## Description

This optimizer does not require analytic derivatives of the fit function. The fully open-source CRAN version of OpenMx offers 2 choices, CSOLNP and SLSQP (from the NLOPT collection). The OpenMx Team's version of OpenMx offers the choice of three optimizers: CSOLNP, SLSQP, and NPSOL.

## Usage

```
mxComputeGradientDescent(freeSet = NA_character_, ..., engine = NULL,
  fitfunction = "fitfunction", verbose = 0L, tolerance = NA_real_,
  useGradient = NULL, warmStart = NULL, nudgeZeroStarts = mxOption(NULL,
  "Nudge zero starts"), maxMajorIter = NULL, gradientAlgo = mxOption(NULL,
  "Gradient algorithm"),
  gradientIterations = imxAutoOptionValue("Gradient iterations"),
  gradientStepSize = imxAutoOptionValue("Gradient step size"))
```

## Arguments

freeSet	names of matrices containing free parameters.
...	Not used. Forces remaining arguments to be specified by name.
engine	specific 'CSOLNP', 'SLSQP', or 'NPSOL'
fitfunction	name of the fitfunction (defaults to 'fitfunction')
verbose	level of debugging output
tolerance	how close to the optimum is close enough (also known as the optimality tolerance)
useGradient	whether to use the analytic gradient (if available)
warmStart	a Cholesky factored Hessian to use as the NPSOL Hessian starting value (preconditioner)
nudgeZeroStarts	whether to nudge any zero starting values prior to optimization (default TRUE)
maxMajorIter	maximum number of major iterations
gradientAlgo	one of c('forward','central')
gradientIterations	number of Richardson iterations to use for the gradient
gradientStepSize	the step size for the gradient

## Details

One option for CSOLNP and SLSQP is gradientAlgo. CSOLNP uses forward method by default, while SLSQP uses central method. forward method requires 1 time gradientIterations function evaluation per parameter per gradient, while central method requires 2 times gradientIterations function evaluations per parameter per gradient. Users can change the default methods for either of these optimizers. NPSOL usually uses the forward method, but adaptively switches to central under certain circumstances.

CSOLNP uses the value of argument gradientStepSize as-is, whereas SLSQP internally scales it by a factor of 100. The purpose of this transformation is to obtain roughly the same accuracy given other differences in numerical procedure. NPSOL ignores gradientStepSize, and instead uses a function of mxOption "Function precision" to determine its gradient step size.

All three optimizers can use analytic gradients, and only NPSOL uses warmStart.

## References

Luenberger, D. G. & Ye, Y. (2008). *Linear and nonlinear programming*. Springer.

## Examples

```
data(demoOneFactor)
factorModel <- mxModel(name = "One Factor",
  mxMatrix(type="Full", nrow=5, ncol=1, free=FALSE, values=0.2, name="A"),
  mxMatrix(type="Symm", nrow=1, ncol=1, free=FALSE, values=1, name="L"),
  mxMatrix(type="Diag", nrow=5, ncol=5, free=TRUE, values=1, name="U"),
  mxAlgebra(expression=A %*% L %*% t(A) + U, name="R"),
  mxExpectationNormal(covariance="R", dimnames=names(demoOneFactor)),
  mxFitFunctionML(),
  mxData(observed=cov(demoOneFactor), type="cov", numObs=500),
  mxComputeSequence(steps=list(
    mxComputeGradientDescent(),
    mxComputeNumericDeriv(),
    mxComputeStandardError(),
    mxComputeHessianQuality()
  )))
factorModelFit <- mxRun(factorModel)
factorModelFit$output$conditionNumber # 29.5
```

---

mxComputeHessianQuality

*Compute the quality of the Hessian*

---

## Description

Tests whether the Hessian is positive definite (model\$output\$infoDefinite) and, if so, computes the approximate condition number (model\$output\$conditionNumber). See Luenberger & Ye (2008) Second Order Test (p. 190) and Condition Number (p. 239).

**Usage**

```
mxComputeHessianQuality(freeSet = NA_character_, ..., verbose = 0L)
```

**Arguments**

freeSet	names of matrices containing free variables
...	Not used. Forces remaining arguments to be specified by name.
verbose	Level of debugging output.

**Details**

The condition number is approximated by  $\text{norm}(H) * \text{norm}(H^{-1})$  where H is the Hessian. The norm is either the 1- or infinity-norm (both obtain the same result due to symmetry).

**References**

Luenberger, D. G. & Ye, Y. (2008). Linear and nonlinear programming. Springer.

---

mxComputeIterate	<i>Repeatedly invoke a series of compute objects until change is less than tolerance</i>
------------------	--

---

**Description**

One step (typically the last) must compute the fit or maxAbsChange.

**Usage**

```
mxComputeIterate(steps, ..., maxIter = 500L, tolerance = 1e-09,
  verbose = 0L, freeSet = NA_character_, maxDuration = as.numeric(NA))
```

**Arguments**

steps	a list of compute objects
...	Not used. Forces remaining arguments to be specified by name.
maxIter	the maximum number of iterations
tolerance	iterates until maximum relative change is less than tolerance
verbose	level of debugging output
freeSet	Names of matrices containing free variables.
maxDuration	the maximum amount of time (in seconds) to iterate

---

mxComputeJacobian	<i>Numerically estimate the Jacobian with respect to free parameters</i>
-------------------	--

---

### Description

When expectations are given, the Jacobian is taken with respect to the manifest model. The manifest model excludes any latent variables or processes. For RAM and LISREL models, the manifest model contains only the manifest variables with free means, covariance, and thresholds. Ordinal manifest variables are standardized.

### Usage

```
mxComputeJacobian(freeSet=NA_character_, ..., of = "expectation", defvar.row=1L)
```

### Arguments

freeSet	names of matrices containing free variables
...	Not used. Forces remaining arguments to be specified by name.
of	a character vector of expectations or algebra names
defvar.row	A row index. Which row to load for definition variables.

### See Also

[omxManifestModelByParameterJacobian](#), [mxGetExpected](#)

---

mxComputeLoadMatrix	<i>Load data from CSV files directly into the backend</i>
---------------------	---

---

### Description

The CSV file must be formatted in a specific way. The number of columns must match the number of entries available in the mxMatrix. Matrix types (e.g., symmetric or diagonal) are respected (see [mxMatrix](#)). For example, a *Full* 2x2 matrix will require 4 entries, but a diagonal matrix of the same size will only require 2 entries. CSV data must be stored space separated and without row or column names. The destination mxMatrix can have free parameters, but cannot have square bracket populated entries.

If originalDataIsIndexOne is TRUE then this compute step does nothing when the loop index is 1. The purpose of originalDataIsIndexOne is to permit usage of the dataset that was initially included with the model.

### Usage

```
mxComputeLoadMatrix(dest, path, ..., originalDataIsIndexOne=FALSE,
  row.names=FALSE, col.names=FALSE)
```

**Arguments**

dest	a character vector of matrix names
path	a character vector of paths
...	Not used. Forces remaining arguments to be specified by name.
originalDataIsIndexOne	logical. Whether to use the initial data for index 1
row.names	logical. Whether row names are present
col.names	logical. Whether column names are present

**See Also**

[mxComputeCheckpoint](#)

**Examples**

```
library(OpenMx)

Cov <- rWishart(4, 20, toeplitz(c(2,1)/20))
write.table(t(apply(Cov, 3, vech)),
            file="cov.csv", col.names=FALSE, row.names=FALSE)
Mean <- matrix(rnorm(8),4,2)
write.table(Mean, file="mean.csv", col.names=FALSE, row.names=FALSE)

m1 <- mxModel(
  "test1",
  mxMatrix("Full", 1,2, values=0, name="mean"),
  mxMatrix("Symm", 2,2, values=diag(2), name="cov"),
  mxMatrix("Full", 1,2, values=-1, name="lbound"),
  mxMatrix("Full", 1,2, values=1, name="ubound"),
  mxAlgebra(omxMnor(cov,mean,lbound,ubound), name="area"),
  mxFitFunctionAlgebra("area"),
  mxComputeLoop(list(
    mxComputeLoadMatrix(c('mean', 'cov'),
                        c('mean.csv', 'cov.csv')),
    mxComputeOnce('fitfunction', 'fit'),
    mxComputeCheckpoint(path="loadMatrix.csv")
  ), i=1:4))

m1 <- mxRun(m1)
```

---

mxComputeLoop

*Repeatedly invoke a series of compute objects*

---

**Description**

When *i* is given then these values are iterated over instead of the sequence 1 to the number of iterations. If *i* is not given then `maxIter` is set to 500 to prevent infinite loops.

**Usage**

```
mxComputeLoop(steps, ..., i = NULL, maxIter = as.integer(NA),
  freeSet = NA_character_, maxDuration = as.numeric(NA))
```

**Arguments**

steps	a list of compute objects
...	Not used. Forces remaining arguments to be specified by name.
i	the values to iterate over
maxIter	the maximum number of iterations
freeSet	Names of matrices containing free variables.
maxDuration	the maximum amount of time (in seconds) to iterate

---

mxComputeNelderMead	<i>Optimize parameters using a variation of the Nelder-Mead algorithm.</i>
---------------------	--

---

**Description**

OpenMx includes a flexible, options-rich implementation of the Nelder-Mead algorithm.

**Usage**

```
mxComputeNelderMead(
  freeSet=NA_character_, fitfunction="fitfunction", verbose=0L,
  nudgeZeroStarts=mxOption(NULL,"Nudge zero starts"),
  maxIter=NULL,...,
  alpha=1, betao=0.5, betai=0.5, gamma=2, sigma=0.5, bignum=1e35,
  iniSimplexType=c("regular","right","smartRight","random"),
  iniSimplexEdge=1, iniSimplexMat=NULL, greedyMinimize=FALSE,
  altContraction=FALSE, degenLimit=0, stagnCtrl=c(-1L,-1L),
  validationRestart=TRUE,
  xTolProx=1e-8, fTolProx=1e-8,
  doPseudoHessian=FALSE,
  ineqConstraintMthd=c("soft","eqMthd"),
  eqConstraintMthd=c("GDsearch","soft","backtrack","l1p"),
  backtrackCtrl=c(0.5,5),
  centerIniSimplex=FALSE)
```

**Arguments**

freeSet	Character-string names of <a href="#">MxMatrices</a> containing free parameters.
fitfunction	Character-string name of the fitfunction; defaults to 'fitfunction'.
verbose	Integer level of reporting printed to terminal at <a href="#">runtime</a> ; defaults to 0.

nudgeZeroStarts	Should free parameters with start values of zero be "nudged" to 0.1 at <code>runtime</code> ? Defaults to the current global value of <code>mxOption</code> "Nudge zero starts". May be a logical value, or one of character strings "Yes" or "No".
maxIter	Integer maximum number of iterations. Value of NULL is accepted, in which case the value used at <code>runtime</code> will be 10 times the number of iterations specified by the effective value of <code>mxOption</code> "Major iterations".
...	Not used. Forces remaining arguments to be specified by name.
alpha	Numeric reflection coefficient. Must be positive. Defaults to 1.0.
betao, betai	Numeric outside- and inside-contraction coefficients, respectively. Both must be within unit interval (0,1). Both default to 0.5.
gamma	Numeric expansion coefficient. If positive, must be greater than alpha. If non-positive, expansion transformations will not be carried out. Defaults to 2.0.
sigma	Numeric shrink coefficient. Cannot exceed 1.0. If non-positive, shrink transformations will not be carried out, and failed contractions will instead be followed by a simplex restart. Defaults to 0.5.
bignum	Numeric value with which the fitfunction value is to be replaced if the fit is non-finite or is evaluated at infeasible parameter values. Defaults to 1e35.
iniSimplexType	Character string naming the method by which to construct the initial simplex from the free-parameter start values. Defaults to "regular".
iniSimplexEdge	Numeric edge-length of the initial simplex. Defaults to 1.0.
iniSimplexMat	Optional numeric matrix providing the vertices of the initial simplex. The matrix must have as many columns as there are free parameters in the <code>MxModel</code> . The matrix's number of rows must be no less than the number of free parameters minus the number of degrees-of-freedom gained from equality <code>MxConstraints</code> , if any. If a non-NULL value is provided, argument <code>iniSimplexEdge</code> is ignored, and argument <code>iniSimplexType</code> is only used in the case of a restart.
greedyMinimize	Logical; should the optimizer use "greedy minimization?" Defaults to FALSE. See below for details.
altContraction	Logical; should the optimizer use an "alternate contraction" transformation? Defaults to FALSE. See below for details.
degenLimit	Numeric "degeneracy limit;" defaults to 0. If positive, the simplex will be restarted if the measure of the angle between any two of its edges is within 0 or pi by less than <code>degenLimit</code> .
stagnCtrl	"Stagnation control;" integer vector of length 2; defaults to <code>c(-1L, -1L)</code> . See below for details.
validationRestart	Logical; defaults to TRUE.
xTolProx	Numeric "domain-convergence" criterion; defaults to 1e-8. See below for details.
fTolProx	Numeric "range-convergence" criterion; defaults to 1e-8. See below for details.
doPseudoHessian	Logical; defaults to FALSE.

ineqConstraintMthd "Inequality constraint method;" character string. Defaults to "soft".

eqConstraintMthd "Equality constraint method;" character string. Defaults to "GDsearch".

backtrackCtrl Numeric vector of length two. See below for details.

centerIniSimplex Logical. If FALSE (default), the MxModel's start values are used as the "first" vertex of the initial simplex. If TRUE, the initial simplex is re-centered so that the MxModel's start values are its eucentroid. However, if iniSimplexMat is non-NULL or if iniSimplexType="smartRight", a value of TRUE is treated as FALSE.

## Details

The state of a Nelder-Mead optimization problem is represented by a simplex (polytope) of  $n + 1$  vertices in the space of the free parameters, where  $n$  is the number of free parameters minus the number of degrees-of-freedom gained from equality [MxConstraints](#). An iteration of the algorithm first sorts the  $n + 1$  vertices by their corresponding fitfunction values (i.e., the values of the fitfunction when evaluated at each vertex), in ascending order (i.e., from "best" fit to "worst" fit). Then, the "subcentroid," which is the centroid of the "best"  $n$  vertices, is calculated. Then, the algorithm attempts to improve upon the worst fit by transforming the simplex; see [Singer & Nelder \(2009\)](#) for details.

Argument iniSimplexType dictates how the initial simplex will be constructed from the start values if argument iniSimplexMat is NULL, and how the simplex will be re-initialized in the case of a restart. In all four cases, the vector of start values constitutes the "starting vertex" of the initial simplex. If iniSimplexType="regular", the initial simplex is merely a regular simplex with edge length equal to iniSimplexEdge. A "right" simplex is constructed by incrementing each free parameter by iniSimplexEdge from its starting value; thus, all the edges that intersect at the starting vertex do so at right angles. A "smartRight" simplex is constructed similarly, except that each free parameter is both incremented *and* decremented by iniSimplexEdge, and of those two points the one with the smaller fitfunction value is retained as a vertex. A "random" simplex is constructed by randomly perturbing the start values, in a manner similar to the default for [mxTryHard\(\)](#), to generate the coordinates of the other vertices. The user is advised that bounds on the free parameters may keep the initial simplex from having the requested regularity or edge-length, and that iniSimplexType is at best a *suggestion* in the presence of equality [MxConstraints](#).

Note that if argument iniSimplexMat has nonzero length, the actual start values of the MxModel's free parameters are not used as a vertex of the initial simplex (unless one of the rows of iniSimplexMat happens to contain those start values).

If the simplex is restarted, a new simplex is constructed per argument iniSimplexType, with edge length equal to the distance between the current best and second-best vertices, and with the current best vertex used as the "first" vertex.

If greedyMinimize=FALSE, "greedy expansion" (Singer & Singer, 2004) is used: if the expansion point and reflection point both have smaller fitfunction values than the best vertex, the expansion point is accepted. If greedyMinimize=TRUE, "greedy minimization" (Singer & Singer, 2004) is used: if the expansion point and the reflection point both have smaller fitfunction values than the best vertex, the better of the two new points is accepted.



If argument `altContraction=TRUE`, the "modified contraction step" of Gill et al. (1982, Chapter 4) is used, and the candidate point is contracted toward the best vertex instead of toward the subcentroid.

If positive, the first element of argument `stagnCtrl` sets a threshold for the number of successive iterations in which the best vertex of the simplex does not change, after which the algorithm is said to be "stagnant" (in a sense similar to that of Kelley, 1999). To attempt to remedy the stagnation, the simplex is restarted. If positive, the second element of argument `stagnCtrl` sets threshold for the number of restarts conducted, beyond which stagnation no longer triggers a restart. The rationale for the second element is that the best vertex may not change for many iterations when the optimizer is close to convergence, under which circumstances restarting would be counterproductive, and in any event would require additional fitfunction evaluations.

If argument `validationRestart=TRUE`, then when the optimizer has successfully converged, it will restart the simplex and attempt to improve upon the tentative solution it already found. This validation restart (Gill et al., 1982, Chapter 4) always re-initializes the simplex as a regular simplex, centered on the best vertex of the tentative solution, with edge-length equal to the distance between the best and worst vertices of the tentative solution. Optimization proceeds until convergence to a solution with a better fit value, or  $2n$  iterations have elapsed.

The Nelder-Mead optimizer is considered to have successfully converged if (1) the largest  $l$ -infinity norm of the vector-differences between the best vertex and the other vertices is less than argument `xTolProx`, or (2) if the largest absolute difference in fit value between the best vertex and the other vertices is less than `fTolProx`.

If argument `doPseudoHessian=TRUE`, there are no equality `MxConstraints`, and the "llp" method (see below) is not in use for inequality `MxConstraints`, then OpenMx will attempt to calculate the "pseudo-Hessian" or "curvature" matrix as described in the appendix to Nelder & Mead (1965). If successful, this matrix will be stored in the 'output' slot of the post-run `MxComputeNelderMead` object. Although crude, its inverse can be used as an estimate of the repeated-sampling covariance matrix of the free parameters when the usual finite-differences Hessian is unreliable.

OpenMx's implementation of Nelder-Mead can handle nonlinear inequality `MxConstraints` reasonably well. Its default method for doing so, with argument `ineqConstraintMthd="soft"`, imposes a "soft" feasibility constraint by assigning a fitfunction value of `bignum` to points that violate the constraints by more than `mxOption 'Feasibility tolerance'`. Alternately, with argument `ineqConstraintMthd="eqMthd"`, inequality `MxConstraints` can be handled by the same method provided to argument `eqConstraintMthd`, whether or not equality `MxConstraints` are present.

OpenMx's implementation of Nelder-Mead respects equality `MxConstraints`, but does not handle them especially well. Its effectiveness at handling equalities may be improved by providing a matrix to argument `iniSimplexMat` that ensures *all* of the initial vertices are feasible. Users are warned that this Nelder-Mead implementation will not work correctly with `MxModels` containing redundant equality `MxConstraints`, and presently has no way of detecting whether any are present. If argument `eqConstraintMthd="GDsearch"` (the default), then whenever Nelder-Mead evaluates the fitfunction at an infeasible point, it initiates a subsidiary optimization that uses `SLSQP` to find the nearest (in squared Euclidean distance) feasible point, and replaces that feasible point for the infeasible one. The user should note that the function evaluations that occur during this subsidiary optimization are counted toward the total number of fitfunction evaluations during the call to `mxRun()`. The effectiveness of the 'GDsearch' method is often improved by setting `mxOption 'Feasibility tolerance'` to a stricter (smaller) value than the on-load default. The method specified by `eqConstraintMthd="soft"` is described in the preceding paragraph. If argument `eqConstraintMthd="backtrack"`, then the optimizer attempts to backtrack from an infeasible

point to a feasible point in a manner similar to that of Ghiasi et al. (2008), except that it used with *all* new points, and not just those encountered via reflection, expansion and contraction. In this case, the displacement from the prior point to the candidate point is reduced by the proportion provided as the first element of argument `backtrackCtrl`, and thus a new candidate point is considered. This process is repeated until feasibility of the candidate point is restored, or the number of attempts exceeds the second element of argument `backtrackCtrl`. If argument `eqConstraintMthd="l1p"`, Nelder-Mead is used as part of an  $l_1$ -penalty algorithm. When using "l1p", the simplex gradient (Kelley, 1999) and "pseudo-Hessian" are never calculated.

### Value

Returns an object of class 'MxComputeNelderMead'.

### References

- Ghiasi, H., Pasini, D., & Lessard, L. (2008). Constrained globalized Nelder-Mead method for simultaneous structural and manufacturing optimization of a composite bracket. *Journal of Composite Materials*, 42(7), p. 717-736. doi: 10.1177/0021998307088592
- Gill, P. E., Murray, W., & Wright, M. H. (1982). *Practical Optimization*. Bingley, UK: Emerald Group Publishing Ltd.
- Kelley, C. T. (1999). Detection and remediation of stagnation in the Nelder-Mead algorithm using a sufficient decrease condition. *SIAM Journal of Optimization* 10(1), p. 43-55.
- Nelder, J. A., & Mead, R. (1965) . A simplex method for function minimization. *The Computer Journal*, 7, p. 308-313.
- Singer, S., & Nelder, J. (2009). Nelder-Mead algorithm. *Scholarpedia*, 4(7):2928., revision #91557. [http://www.scholarpedia.org/article/Nelder-Mead\\_algorithm](http://www.scholarpedia.org/article/Nelder-Mead_algorithm) .
- Singer, S., & Singer, S. (2004). Efficient implementation of the Nelder-Mead search algorithm. *Applied Numerical Analysis & Computational Mathematics Journal*, 1(2), p. 524-534. doi: 10.1002/anac.200410015

### Examples

```
foo <- mxComputeNelderMead()
str(foo)
```

---

mxComputeNewtonRaphson

*Optimize parameters using the Newton-Raphson algorithm*

---

### Description

This optimizer requires analytic 1st and 2nd derivatives of the fit function. Box constraints are supported. Parameters can approach box constraints but will not leave the feasible region (even by some small  $\epsilon > 0$ ). Non-finite fit values are interpreted as soft feasibility constraints. That is, when a non-finite fit is encountered, line search is continued after the step size is multiplied by 10 available by increasing the verbose level.

**Usage**

```
mxComputeNewtonRaphson(freeSet = NA_character_, ...,
  fitfunction = "fitfunction", maxIter = 100L, tolerance = 1e-12,
  verbose = 0L)
```

**Arguments**

freeSet	names of matrices containing free variables
...	Not used. Forces remaining arguments to be specified by name.
fitfunction	name of the fitfunction (defaults to 'fitfunction')
maxIter	maximum number of iterations
tolerance	optimization is considered converged when the maximum relative change in fit is less than tolerance
verbose	level of debugging output

**References**

Luenberger, D. G. & Ye, Y. (2008). *Linear and nonlinear programming*. Springer.

---

mxComputeNothing	<i>Compute nothing</i>
------------------	------------------------

---

**Description**

Note that this compute plan actually does nothing whereas `mxComputeOnce("expectation", "nothing")` may remove the prediction of an expectation.

**Usage**

```
mxComputeNothing()
```

---

mxComputeNumericDeriv	<i>Numerically estimate Hessian using Richardson extrapolation</i>
-----------------------	--

---

**Description**

For N free parameters, Richardson extrapolation requires (iterations \* (N<sup>2</sup> + N)) function evaluations. The implementation is closely based on the numDeriv R package.

**Usage**

```
mxComputeNumericDeriv(freeSet = NA_character_, ...,
  fitfunction = "fitfunction", parallel = TRUE,
  stepSize = imxAutoOptionValue("Gradient step size"), iterations = 4L,
  verbose = 0L, knownHessian = NULL, checkGradient = TRUE,
  hessian = TRUE)
```

**Arguments**

freeSet	names of matrices containing free variables
...	Not used. Forces remaining arguments to be specified by name.
fitfunction	name of the fitfunction (defaults to 'fitfunction')
parallel	whether to evaluate the fitfunction in parallel (defaults to TRUE)
stepSize	starting set size (defaults to 0.0001)
iterations	number of Richardson extrapolation iterations (defaults to 4L)
verbose	Level of debugging output.
knownHessian	an optional matrix of known Hessian entries
checkGradient	whether to check the first order convergence criterion (gradient is near zero)
hessian	whether to estimate the Hessian. If FALSE then only the gradient is estimated.

**Details**

In addition to an estimate of the Hessian, forward, central, and backward estimates of the gradient are made available in this compute plan's output slot.

When checkGradient=TRUE, the central difference estimate of the gradient is used to determine whether the first order convergence criterion is met. In addition, the forward and backward difference estimates of the gradient are compared for symmetry. When sufficient asymmetry is detected, the standard error is flagged. In the case, profile likelihood confidence intervals should be used for inference instead of standard errors (see mxComputeConfidenceInterval).

**Examples**

```
library(OpenMx)
data(demoOneFactor)
factorModel <- mxModel(name = "One Factor",
  mxMatrix(type = "Full", nrow = 5, ncol = 1, free = FALSE, values = .2, name = "A"),
  mxMatrix(type = "Symm", nrow = 1, ncol = 1, free = FALSE, values = 1, name = "L"),
  mxMatrix(type = "Diag", nrow = 5, ncol = 5, free = TRUE, values = 1, name = "U"),
  mxAlgebra(A %*% L %*% t(A) + U, name = "R"),
  mxExpectationNormal(covariance = "R", dimnames = names(demoOneFactor)),
  mxFitFunctionML(),
  mxData(cov(demoOneFactor), type = "cov", numObs = 500),
  mxComputeSequence(
    list(mxComputeNumericDeriv(), mxComputeReportDeriv())
  )
)
factorModelFit <- mxRun(factorModel)
factorModelFit$output$hessian
```

---

mxComputeOnce	<i>Compute something once</i>
---------------	-------------------------------

---

### Description

Some models are optimized for a sparse Hessian. Therefore, it can be much more efficient to compute the inverse Hessian in comparison to computing the Hessian and then inverting it.

### Usage

```
mxComputeOnce(from, what = NULL, how = NULL, ..., freeSet = NA_character_,
  verbose = 0L, .is.bestfit = FALSE)
```

### Arguments

from	the object to perform the computation (a vector of expectation or fit function names)
what	what to compute
how	to compute it (optional)
...	Not used. Forces remaining arguments to be specified by name.
freeSet	names of matrices containing free variables
verbose	the level of debugging output
.is.bestfit	do not use; for backward compatibility

### Details

The information matrix is only valid when parameters are at the maximum likelihood estimate. The information matrix is returned in `model$output$hessian`. You cannot request both the information matrix and the Hessian. The information matrix is invariant to the sign of the log likelihood scale whereas the Hessian is not. Use the `how` parameter to specify which approximation to use (one of "default", "hessian", "sandwich", "bread", and "meat").

### Examples

```
data(demoOneFactor)
factorModel <- mxModel(name = "One Factor",
  mxMatrix(type="Full", nrow=5, ncol=1, free=TRUE, values=0.2, name="A"),
  mxMatrix(type="Symm", nrow=1, ncol=1, free=FALSE, values=1, name="L"),
  mxMatrix(type="Diag", nrow=5, ncol=5, free=TRUE, values=1, name="U"),
  mxAlgebra(expression=A %*% L %*% t(A) + U, name="R"),
  mxFitFunctionML(), mxExpectationNormal(covariance="R", dimnames=names(demoOneFactor)),
  mxData(observed=cov(demoOneFactor), type="cov", numObs=500),
  mxComputeOnce('fitfunction', 'fit'))
factorModelFit <- mxRun(factorModel)
factorModelFit$output$fit # 972.15
```

---

mxComputeReportDeriv *Report derivatives*

---

**Description**

Copy the internal gradient and Hessian back to R.

**Usage**

```
mxComputeReportDeriv(freeSet = NA_character_)
```

**Arguments**

freeSet            names of matrices containing free variables

---

mxComputeReportExpectation  
*Report expectation*

---

**Description**

Copy the internal model expectations back to R.

**Usage**

```
mxComputeReportExpectation(freeSet = NA_character_)
```

**Arguments**

freeSet            names of matrices containing free variables

---

mxComputeSequence *Invoke a series of compute objects in sequence*

---

**Description**

Invoke a series of compute objects in sequence

**Usage**

```
mxComputeSequence(steps = list(), ..., freeSet = NA_character_,  
                  independent = FALSE)
```

**Arguments**

steps	a list of compute objects
...	Not used; forces argument 'freeSet' to be specified by name.
freeSet	Names of matrices containing free parameters.
independent	Whether the steps could be executed out-of-order.

---

mxComputeSimAnnealing *Optimization using generalized simulated annealing*

---

**Description**

Performs simulated annealing to minimize the fit function. If the original starting values are outside of the feasible set, a few attempts are made to find viable starting values.

**Usage**

```
mxComputeSimAnnealing(freeSet=NA_character_, ..., fitfunction='fitfunction',
  plan=mxComputeOnce('fitfunction','fit'),
  verbose=0L, method=c("tsallis1996", "ingber2012"), control=list(),
  defaultGradientStepSize=mxAutoOptionValue("Gradient step size"),
  defaultFunctionPrecision=mxAutoOptionValue("Function precision"))
```

**Arguments**

freeSet	names of matrices containing free variables
...	Not used. Forces remaining arguments to be specified by name.
fitfunction	name of the fitfunction (defaults to 'fitfunction')
plan	compute plan to optimize the model
verbose	level of debugging output
method	which algorithm to use
control	control parameters specific to the chosen method
defaultGradientStepSize	the default gradient step size
defaultFunctionPrecision	the default function precision

**Details**

For method 'tsallis1996', the number of function evaluations are determined by the tempStart and tempEnd parameters. There is no provision to stop early because there is no way to determine whether the algorithm has converged. The Markov step is implemented by cycling through each parameters in turn and considering a univariate jump (like a Gibbs sampler).

Control parameters include qv to control the shape of the visiting distribution, qaInit to control the shape of the initial acceptance distribution, lambda to reduce the probability of acceptance

in time, tempStart to specify starting temperature, tempEnd to specify ending temperature, and stepsPerTemp to set the number of Markov steps per temperature step.

Non-linear constraints are accommodated by a penalty function. Inequality constraints work reasonably well, but equality constraints do not work very well. Constrained optimization will likely require increasing stepsPerTemp.

Classical simulated annealing (CSA) can be obtained with qv=qa=1 and lambda=0. Fast simulated annealing (FSA) can be obtained with qv=2, qa=1, and lambda=0. FSA is faster than CSA, but GSA is faster than FSA. GenSA default parameters are set to those identified in Xiang, Sun, Fan & Gong (1997).

Method 'ingber2012' has spawned a cultural tradition over more than 30 years that is documented in Aguiar e Oliveira et al (2012). Options are specified using the traditional option names in the control list. However, there are a few option changes to make ASA fit better with OpenMx. Instead of option Curvature\_0, use [mxComputeNumericDeriv](#). ASA\_PRINT output is directed to /dev/null by default. To direct ASA\_PRINT output to console use control=list('Asa\_Out\_File' = '/dev/fd/1'). ASA's option to control the finite differences gradient step size, Delta\_X, defaults to [mxOption](#)'s 'Gradient step size' instead of ASA's traditional 0.001. Similarly, Cost\_Precision defaults to [mxOption](#)'s 'Function Precision' instead of ASA's traditional 1e-18.

## References

- Aguiar e Oliveira, H., Ingber, L., Petraglia, A., Petraglia, M. R., & Machado, M. A. S. (2012). *Stochastic global optimization and its applications with fuzzy adaptive simulated annealing*. Springer Publishing Company, Incorporated.
- Tsallis, C., & Stariolo, D. A. (1996). Generalized simulated annealing. *Physica A: Statistical Mechanics and its Applications*, 233(1-2), 395-406.
- Xiang, Y., Sun, D. Y., Fan, W., & Gong, X. G. (1997). Generalized simulated annealing algorithm and its application to the Thomson model. *Physics Letters A*, 233(3), 216-220.

## See Also

[mxComputeTryHard](#)

## Examples

```
library(OpenMx)
m1 <- mxModel(
  "poly22", # Eqn 22 from Tsallis & Stariolo (1996)
  mxMatrix(type='Full', values=runif(4, min=-1e6, max=1e6),
    ncol=1, nrow=4, free=TRUE, name='x'),
  mxAlgebra(sum((x*x-8)^2) + 5*sum(x) + 57.3276, name="fit"),
  mxFitFunctionAlgebra('fit'),
  mxComputeSimAnnealing())

m1 <- mxRun(m1)
summary(m1)
```



---

 mxComputeStandardError

*Compute standard errors*


---

### Description

When the fit is in -2 log likelihood units, the SEs are derived from the diagonal of the Hessian or inverse Hessian. The Hessian (in some form) must already be available.

### Usage

```
mxComputeStandardError(freeSet = NA_character_, fitfunction = "fitfunction")
```

### Arguments

freeSet	names of matrices containing free variables
fitfunction	name of the fitfunction (defaults to 'fitfunction')

---

 mxComputeTryHard

*Repeatedly attempt a compute plan until successful*


---

### Description

The provided compute plan is run until the status code indicates success (0 or 1). It gives up after a small number of retries.

### Usage

```
mxComputeTryHard(plan, ..., freeSet = NA_character_, verbose = 0L,
  location = 1, scale = 0.25, maxRetries = 3L)
```

### Arguments

plan	compute plan to optimize the model
...	Not used. Forces remaining arguments to be specified by name.
freeSet	names of matrices containing free variables
verbose	level of debugging output
location	location of the perturbation distribution
scale	scale of the perturbation distribution
maxRetries	maximum number of plan evaluations per invocation (including the first evaluation)

## Details

Upon failure, start values are randomly perturbed. Currently only the uniform distribution is implemented. The distribution is parametrized by arguments `location` and `scale`. The location parameter is the distribution's median. For the uniform distribution, `scale` is the absolute difference between its median and extrema (i.e., half the width of the rectangle). Each start value is multiplied by a random draw and then added to a random draw from a distribution with the same `scale` but with a median of zero.

## References

Shanno, D. F. (1985). On Broyden-Fletcher-Goldfarb-Shanno method. *Journal of Optimization Theory and Applications*, 46(1), 87-94.

## See Also

[mxTryHard](#)

---

<code>mxConstraint</code>	<i>Create MxConstraint Object</i>
---------------------------	-----------------------------------

---

## Description

This function creates a new [MxConstraint](#) object.

## Usage

```
mxConstraint(expression, name=NA, ..., jac=character(0))
```

## Arguments

<code>expression</code>	The <a href="#">MxAlgebra</a> -like expression representing the constraint function.
<code>name</code>	An optional character string indicating the name of the object.
<code>...</code>	Not used. Helps <code>OpenMx</code> catch bad input to argument <code>expression</code> , and requires argument <code>jac</code> —meant for advanced users—to be specified by name.
<code>jac</code>	An optional character string naming the <a href="#">MxAlgebra</a> or <a href="#">MxMatrix</a> representing the Jacobian for the constraint function.

## Details

The `mxConstraint()` function defines relationships between two [MxAlgebra](#) or [MxMatrix](#) objects. They are used to affect the estimation of free parameters in the referenced objects. The constraint relation is written identically to how a [MxAlgebra](#) expression would be written. The outermost operator in this relation must be either `<`, `==` or `>`. To affect an estimation or optimization, an [MxConstraint](#) object must be included in an [MxModel](#) object with all referenced [MxAlgebra](#) and [MxMatrix](#) objects.

Usage Note: Use of `mxConstraint()` should be avoided where it is possible to achieve the constraint by equating free parameters by label or position in an `MxMatrix` or `MxAlgebra` object. Including `mxConstraints` in an `mxModel` will disable standard errors and the calculation of the final Hessian, and thus should be avoided when standard errors are of importance. Constraints also add computational overhead. If one labels two parameters the same, the optimizer has one fewer parameter to optimize. However, if one uses `mxConstraint` to do the same thing, both parameters remain estimated and a Lagrangian multiplier is added to maintain the constraint. This constraint also has to have its gradients computed and the order of the Hessian grows as well. So while both approaches should work, the `mxConstraint()` will take longer to do so.

Alternatives to `mxConstraints` include using labels, `lbound` or `ubound` arguments or algebras. Free parameters in the same `MxModel` may be constrained to equality by giving them the same name in their respective 'labels' matrices. Similarly, parameters may be fixed to an individual element in a `MxModel` object or the result of an `MxAlgebra` object through labeling. For example, assigning a label of "name[1,1]" fixes the value of a parameter at the value in first row and first column of the matrix or algebra "name". The `mxConstraint` function should be used to enforce inequalities that cannot be conveyed using other methods.

Note that constraints imposed on functions of `definition variables` will only be operative for a single row of the dataset, and *not* for all rows of the dataset.

Argument `jac` is used to provide the name of an `MxMatrix` or `MxAlgebra` that equals the matrix of first derivatives—the Jacobian—of the constraint function with respect to the free parameters. Here, the "constraint function" refers to the constraint expression in canonical form: an arbitrary matrix expression on the left-hand side of the comparator, and a matrix of zeroes with the same dimensions on the right-hand side. The rows of the Jacobian correspond to elements of the matrix result of the right-hand side, in column-major order. Each row of the Jacobian is the vector of first partial derivatives, with respect to the free parameters of the `MxModel`, of its corresponding element. Each column of the Jacobian corresponds to a free parameter of the `MxModel`; each column must be named with the label of the corresponding free parameter. All the `gradient-descent` optimizers are able to take advantage of user-supplied Jacobians.

If you provide analytic Jacobians for inequality constraints with SLSQP, the inequality constraints must use the "less than" comparator. Providing analytic Jacobians for inequality constraints with NPSOL is recommended only for expert users. Apparently, when there are no equality constraints, NPSOL expects the Jacobians of inequality constraints to be defined as though the constraints used the "less than" comparator, whereas if there *are* equality constraints, NPSOL expects the Jacobians of the inequality constraints to be defined as though the constraints used the "greater than" comparator.

## Value

Returns an `MxConstraint` object.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

`MxConstraint` for the S4 class created by `mxConstraint`.

## Examples

```

library(OpenMx)

#Create a constraint between MxMatrices 'A' and 'B'
constraint <- mxConstraint(A > B, name = 'AdominatesB')

# Constrain matrix 'K' to be equal to matrix 'limit'

model <- mxModel(model="con_test",
  mxMatrix(type="Full", nrow=2, ncol=2, free=TRUE, name="K"),
  mxMatrix(type="Full", nrow=2, ncol=2, free=FALSE, name="limit", values=1:4),
  mxConstraint(K == limit, name = "Klimit_equality"),
  mxAlgebra(min(K), name="minK"),
  mxFitFunctionAlgebra("minK")
)

fit <- mxRun(model)
fit$matrices$K$values

#      [,1] [,2]
# [1,]   1   3
# [2,]   2   4

# Constrain both free parameters of a matrix to equality using labels (both are set to "eq")
equal <- mxMatrix("Full", 2, 1, free=TRUE, values=1, labels="eq", name="D")

# Constrain a matrix element in to be equal to the result of an algebra
start <- mxMatrix("Full", 1, 1, free=TRUE, values=1, labels="param", name="F")
alg <- mxAlgebra(log(start), name="logP")

# Force the fixed parameter in matrix G to be the result of the algebra
end <- mxMatrix("Full", 1, 1, free=FALSE, values=1, labels="logP[1,1]", name="G")

```

---

MxConstraint-class      *Class "MxConstraint"*

---

## Description

MxConstraint is an S4 class. An MxConstraint object is a [named entity](#). New instances of this class can be created using the function `mxConstraint()`.

## Details

Slots may be referenced with the \$ symbol. See the documentation for [Classes](#) and the examples in the [mxConstraint](#) document for more information.

**Slots**

- name:** Character string; the name of the object.
- formula:** Object of class "MxAlgebraFormula". The [MxAlgebra](#)-like expression representing the constraint function.
- alg1:** Object of class "MxCharOrNumber". For internal use.
- alg2:** Object of class "MxCharOrNumber". For internal use.
- relation:** Object of class "MxCharOrNumber". For internal use.
- jac:** Object of class "MxCharOrNumber". Identifies the [MxAlgebra](#) representing the Jacobian for the constraint function.
- linear:** Logical. For internal use.

**Methods**

```

$<- signature(x = "MxConstraint")
$ signature(x = "MxConstraint")
imxDeparse signature(object = "MxConstraint")
names signature(x = "MxConstraint")
print signature(x = "MxConstraint")
show signature(object = "MxConstraint")

```

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

[mxConstraint\(\)](#) for the function that creates MxConstraint objects.

**Examples**

```
showClass("MxConstraint")
```

---

mxData

*Create MxData Object*


---

**Description**

This function creates a new [MxData](#) object. (for WLS data see [mxDataWLS](#)).

**Usage**

```

mxData(observed, type, means = NA, numObs = NA, acov=NA, fullWeight=NA,
        thresholds=NA, ..., sort=NA, primaryKey = as.character(NA),
        weight = as.character(NA), frequency = as.character(NA))

```

**Arguments**

observed	A matrix or data.frame which provides data to the MxData object.
type	A character string defining the type of data in the ‘observed’ argument. Must be one of “raw”, “cov”, “cor”, “sscp” or “acov”.
means	An optional vector of means for use when ‘type’ is “cov”, or “cor”.
numObs	The number of observations in the data supplied in the ‘observed’ argument. Required unless ‘type’ equals “raw”.
acov	Asymptotic covariance matrix of observed, means, and thresholds. Used for weighted least squares weight matrix.
fullWeight	Full asymptotic covariance matrix of observed, means, and thresholds. Used for weighted least squares in standard error and quasi-chi-squared calculation.
thresholds	Observed thresholds. Used for weighted least squares with ordinal data.
...	Not used. Forces remaining arguments to be specified by name.
sort	Whether to sort raw data prior to use (default NA)
primaryKey	The column name of the primary key used to uniquely identify rows (default NA)
weight	The column name containing row weights
frequency	The column name containing row frequencies

**Details**

The `mxData` function creates `MxData` objects, which can be used as arguments in `MxModel` objects. The ‘observed’ argument may take either a data frame or a matrix, which is then described with the ‘type’ argument. Data types describe compatibility and usage with expectation functions in `MxModel` objects. Four different data types are supported (a fifth, `sscp`, is not yet implemented):

- raw** The contents of the ‘observed’ argument are treated as raw data. Missing values are permitted and must be designated as the system missing value. The ‘means’ and ‘numObs’ arguments cannot be specified, as the ‘means’ argument is not relevant and the ‘numObs’ argument is automatically populated with the number of rows in the data. Data of this type may use fit functions such as `mxFitFunctionML` function in `MxModel` objects, which will automatically use covariance estimation under full-information maximum likelihood for this data type.
- cov** The contents of the ‘observed’ argument are treated as a covariance matrix. The ‘means’ argument is not required, but may be included for estimations involving means. The ‘numObs’ argument is required, which should reflect the number of observations or rows in the data described by the covariance matrix. Data of this type may use the fit functions such as `mxFitFunctionML`, depending on the specified model.
- cor** The contents of the ‘observed’ argument are treated as a correlation matrix. The ‘means’ argument is not required, but may be included for estimations involving means. The ‘numObs’ argument is required, which should reflect the number of observations or rows in the data described by the covariance matrix. Data of this type may use the fit functions such as `mxFitFunctionML` functions, depending on the specified model.

**acov** The best way to create data of this type is to use the [mxDataWLS](#) function. The contents of the ‘observed’ argument are treated as the polychoric correlation matrix of the ordinal variables. The ‘means’ argument is not required, but may be included for estimations involving means. The ‘thresholds’ argument is not required, but may be included for estimation involving thresholds and ordinal variables. The ‘numObs’ argument is required, which should reflect the number of observations or rows in the data described by the polychoric correlation matrix. Data of this type almost certainly use the [mxFitFunctionWLS](#) function, but may depend on the specified model.

MxData objects may not be included in [MxAlgebra](#) objects or use the [mxFitFunctionAlgebra](#) function. If these capabilities are desired, data should be appropriately input or transformed using the [mxMatrix](#) and [mxAlgebra](#) functions.

While column names are stored in the ‘observed’ slot of MxData objects, these names are not recognized as variable names in [MxPath](#) objects. Variable names must be specified using the ‘manifestVars’ argument of the [mxModel](#) function prior to use in [MxPath](#) objects.

The mxData function does not currently place restrictions on the size, shape, or symmetry of matrices input into the ‘observed’ argument. While it is possible to specify MxData objects as covariance or correlation matrices that do not have the properties commonly associated with these matrices, failure to correctly specify these matrices will likely lead to problems in model estimation.

OpenMx uses the names of variables to map them onto the expectation functions and other elements associated with your model. For data.frames, ensure you have set the names(). For matrices set names using, for instance, row.names=c(“your”, “columns”). Covariance and correlation matrices need to have both the row and column names set and these must be identical, for instance by using `dimnames = list(varNames, varNames)`.

In the case of raw data, the optional ‘weight’ argument names a column in the ‘observed’ data that contains per-row weights. Similarly, the optional ‘frequency’ argument names a column in the ‘observed’ data that contains per-row frequencies. Frequencies must be integral but weights can be arbitrary real numbers. For data with many repeated response patterns, organizing the data into unique patterns and frequencies can reduce model evaluation time.

In some cases, the fit function can be evaluated more efficiently when data are sorted. When a primary key is provided, sorting is disabled. Otherwise, sort defaults to TRUE.

## Value

Returns a new [MxData](#) object.

## References

The OpenMx User’s guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

For WLS data, see [mxDataWLS](#). To generate data, see [mxGenerateData](#); For objects which may be entered as arguments in the ‘observed’ slot, see [matrix](#) and [data.frame](#). See [MxData](#) for the S4 class created by mxData. More information about the OpenMx package may be found [here](#).

## Examples

```

library(OpenMx)

# Create a covariance matrix
covMatrix <- matrix( c(0.77642931, 0.39590663,
  0.39590663, 0.49115615),
  nrow = 2, ncol = 2, byrow = TRUE)
covNames <- c("x", "y")
dimList <- list(covNames, covNames)
dimnames(covMatrix) <- dimList

# Create an MxData object including that covariance matrix
testData <- mxData(observed=covMatrix, type="cov", numObs = 100)

testModel <- mxModel(model="testModel",
  mxMatrix(type="Symm", nrow=2, ncol=2, values=c(.2,.1,.2),
    free=TRUE, name="expCov", dimnames=dimList),
  mxExpectationNormal(covariance="expCov", dimnames=covNames),
  mxFitFunctionML(),
  testData)

outModel <- mxRun(testModel)

summary(outModel)

```

---

MxData-class

*MxData Class*


---

## Description

MxData is an S4 class. An MxData object is a [named entity](#). New instances of this class can be created using the function [mxData](#). MxData is an S4 class union. An MxData object is either [NULL](#) or a MxNonNullData object.

## Details

The MxNonNullData class has the following slots:

- name - The name of the object
- observed - Either a matrix or a data frame
- vector - A vector for means, or NA if missing
- type - Either 'raw', 'cov', or 'cor'
- numObs - The number of observations



The 'name' slot is the name of the MxData object.

The 'observed' slot is used to contain data, either as a matrix or as a data frame. Use of the data in this slot by other functions depends on the value of the 'type' slot. When 'type' is equal to 'cov' or 'cor', the data input into the 'matrix' slot should be a symmetric matrix or data frame.

The 'vector' slot is used to contain a vector of numeric values, which is used as a vector of means for MxData objects with 'type' equal to 'cov' or 'cor'. This slot may be used in estimation using the [mxFitFunctionML](#) function.

The 'type' slot may take one of four supported values:

- raw** The contents of the 'observed' slot are treated as raw data. Missing values are permitted and must be designated as the system missing value. The 'vector' and 'numObs' slots cannot be specified, as the 'vector' argument is not relevant and the 'numObs' argument is automatically populated with the number of rows in the data. Data of this type may use the [mxFitFunctionML](#) function as its fit function in MxModel objects, which can deal with covariance estimation under full-information maximum likelihood.
- cov** The contents of the 'observed' slot are treated as a covariance matrix. The 'vector' argument is not required, but may be included for estimations involving means. The 'numObs' slot is required. Data of this type may use fit functions such as the [mxFitFunctionML](#), depending on the specified model.
- cor** The contents of the 'observed' slot are treated as a correlation matrix. The 'vector' argument is not required, but may be included for estimations involving means. The 'numObs' slot is required. Data of this type may use fit functions such as the [mxFitFunctionML](#), depending on the specified model.

The 'numObs' slot describes the number of observations in the data. If 'type' equals 'raw', then 'numObs' is automatically populated as the number of rows in the matrix or data frame in the 'observed' slot. If 'type' equals 'cov' or 'cor', then this slot must be input using the 'numObs' argument in the [mxData](#) function when the MxData argument is created.

MxData objects may not be included in [MxAlgebra](#) objects or use the [mxFitFunctionAlgebra](#) function. If these capabilities are desired, data should be appropriately input or transformed using the [mxMatrix](#) and [mxAlgebra](#) functions.

While column names are stored in the 'observed' slot of MxData objects, these names are not recognized as variable names in [MxPath](#) objects. Variable names must be specified using the 'manifestVars' argument of the [mxModel](#) function prior to use in [MxPath](#) objects.

The [mxData](#) function does not currently place restrictions on the size, shape, or symmetry of matrices input into the 'observed' argument. While it is possible to specify MxData objects as covariance or correlation matrices that do not have the properties commonly associated with these matrices, failure to correctly specify these matrices will likely lead to problems in model estimation.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

[mxData](#) for creating MxData objects, [matrix](#) and [data.frame](#) for objects which may be entered as arguments in the 'matrix' slot. More information about the OpenMx package may be found [here](#).

---

mxDataDynamic	<i>Create dynamic data</i>
---------------	----------------------------

---

**Description**

Create dynamic data

**Usage**

```
mxDataDynamic(type, ..., expectation, verbose = 0L)
```

**Arguments**

type	type of data
...	Not used. Forces remaining arguments to be specified by name.
expectation	the name of the expectation to provide the data
verbose	Increase runtime debugging output

---

MxDataFrameOrMatrix-class	<i>MxDataFrameOrMatrix</i>
---------------------------	----------------------------

---

**Description**

Internal class that is the union of data.frame and matrix.

**Details**

Not to be used.

---

MxDataStatic-class	<i>Create static data</i>
--------------------	---------------------------

---

**Description**

Internal static data class.

**Details**

Not to be used.

mxDataWLS

*Create MxData Object for Least Squares (WLS, DWLS, ULS) Analyses***Description**

This function creates a new [MxData](#) object of type “ULS” (unweighted least squares), “WLS” (weighted least squares) or “DWLS” (diagonally-weighted least squares). The appropriate fit function to include with these models is [mxFitFunctionWLS](#)

**Usage**

```
mxDataWLS(data, type = "WLS", useMinusTwo = TRUE, returnInverted = TRUE,
  fullWeight = TRUE, suppressWarnings = TRUE, allContinuousMethod =
  "cumulants", ..., silent=!interactive())
```

**Arguments**

data	A matrix or data.frame which provides raw data to be used for WLS.
type	A character string 'WLS' (default), 'DWLS', or 'ULS' for weighted, diagonally weighted, or unweighted least squares, respectively
useMinusTwo	Logical indicating whether to use -2LL (default) or -LL.
returnInverted	Logical indicating whether to return the information matrix (default) or the covariance matrix.
fullWeight	Logical determining if the full weight matrix is returned (default). Needed for standard error and quasi-chi-squared calculation.
suppressWarnings	Logical that determines whether to suppress diagnostic warnings. These warnings are likely only helpful to developers.
allContinuousMethod	A character string 'cumulants' (default) or 'marginals'. See Details.
...	Not used. Forces remaining arguments to be specified by name.
silent	Whether to report progress

**Details**

The `mxDataWLS` function creates an [MxData](#) object, which can be used in [MxModel](#) objects. This function takes raw data and returns an `MxData` object to be used in a model to fit with weighted least squares.

Both Ordinal and continuous data are supported. A combination of these data types also succeeds. Early tests suggested that full 'WLS' might be biased in this joint ordinal and continuous case, whereas 'ULS' and 'DWLS' were unbiased. However further investigation revealed that all of these were unbiased when the model is correct, but full 'WLS' is highly sensitive to model misspecification. Full 'WLS' can heavily weight the fourth-order moments of the distribution, so small deviations between the observed fourth-order moments and those implied by the model can lead to poor estimates.

By default when only continuous variables are present, the argument `allContinuousMethod` dictates that the asymptotically distribution free (ADF) method of Browne (1984) is used. This method computes the fourth order *cumulants* for the weight matrix: thus, the name. The method does not readily handle missing data and does not return weights or summary statistics for the means, but it is generally fast and ADF up to elliptical distributions. The other option, 'marginals', uses similar methods to the ordinal and joint ordinal-continuous cases. It does return weights and summary statistics for the means. When there are any ordinal variables present, `allContinuousMethod` is ignored.

### Value

Returns a new `MxData` object.

### References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

Browne, M. W. (1984). Asymptotically distribution-free methods for the analysis of covariance structures. *British Journal of Mathematical and Statistical Psychology*, 37, p. 62-83.

### See Also

`mxFitFunctionWLS`. `MxData` for the S4 class created by `mxData`. `matrix` and `data.frame` for objects which may be entered as arguments in the 'observed' slot. More information about the OpenMx package may be found [here](#).

### Examples

```
# Create and fit a model using mxMatrix, mxAlgebra, mxExpectationNormal, and mxFitFunctionWLS

library(OpenMx)

# Simulate some data

x=rnorm(1000, mean=0, sd=1)
y= 0.5*x + rnorm(1000, mean=0, sd=1)
tmpFrame <- data.frame(x, y)
tmpNames <- names(tmpFrame)
wdata <- mxDataWLS(tmpFrame)

# Define the matrices

S <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(1,0,0,1),
              free=c(TRUE,FALSE,FALSE,TRUE), labels=c("Vx", NA, NA, "Vy"), name = "S")
A <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(0,1,0,0),
              free=c(FALSE,TRUE,FALSE,FALSE), labels=c(NA, "b", NA, NA), name = "A")
I <- mxMatrix(type="Iden", nrow=2, ncol=2, name="I")

# Define the expectation
```

```

expCov <- mxAlgebra(solve(I-A) %*% S %*% t(solve(I-A)), name="expCov")
expFunction <- mxExpectationNormal(covariance="expCov", dimnames=tmpNames)

# Choose a fit function

fitFunction <- mxFitFunctionWLS()

# Define the model

tmpModel <- mxModel(model="exampleModel", S, A, I, expCov, expFunction, fitFunction,
                    wdata)

# Fit the model and print a summary

tmpModelOut <- mxRun(tmpModel)
summary(tmpModelOut)

```

---

MxDirectedGraph-class *MxDirectedGraph*

---

### Description

This is an internal class and should not be used directly. It is a class for directed graphs.

---

mxEval *Evaluate Values in MxModel*

---

### Description

This function can be used to evaluate an arbitrary R expression that includes named entities from a [MxModel](#) object, or labels from a [MxMatrix](#) object.

### Usage

```
mxEval(expression, model, compute = FALSE, show = FALSE, defvar.row = 1,
        cache = new.env(parent = emptyenv()), cacheBack = FALSE)
```

```
mxEvalByName(name, model, compute = FALSE, show = FALSE, defvar.row = 1,
             cache = new.env(parent = emptyenv()), cacheBack = FALSE)
```

### Arguments

expression	An arbitrary R expression.
model	The model in which to evaluate the expression.
compute	If TRUE then compute the value of algebra expressions and populate square bracket substitutions.

show	If TRUE then print the translated expression.
defvar.row	The row number for definition variables when compute=TRUE; defaults to 1. When compute=FALSE, values for definition variables are always taken from the first (i.e., first before any automated sorting is done) row of the raw data.
cache	An R environment of matrix values used to speedup computation.
cacheBack	If TRUE then return the list pair (value, cache).
name	The character name of an object to evaluate.

### Details

The argument ‘expression’ is an arbitrary R expression. Any named entities that are used within the R expression are translated into their current value from the model. Any labels from the matrices within the model are translated into their current value from the model. Finally the expression is evaluated and the result is returned. To enable debugging, the ‘show’ argument has been provided. The most common mistake when using this function is to include named entities in the model that are identical to R function names. For example, if a model contains a named entity named ‘c’, then the following mxEval call will return an error: `mxEval(c(A, B, C), model)`.

The `mxEvalByName` function is a wrapper around `mxEval` that takes a character instead of an R expression.

If ‘compute’ is FALSE, then MxAlgebra expressions return their current values as they have been computed by the optimization call (using `mxRun`). If the ‘compute’ argument is TRUE, then MxAlgebra expressions will be calculated in R and square bracket substitutions will be performed. Any references to an objective function that has not yet been calculated will return a 1 x 1 matrix with a value of NA.

The ‘cache’ is used to speedup calculation by storing previously computing values. The cache is a list of matrices, such that `names(cache)` must all be of the form “modelname.entityname”. Setting ‘cacheBack’ to TRUE will return the pair `list(value, cache)` where value is the result of the `mxEval()` computation and cache is the updated cache.

### References

The OpenMx User’s guide can be found at <http://openmx.ssri.psu.edu/documentation>.

### See Also

[mxAlgebra](#) to create algebraic expressions inside your model and [mxModel](#) for the model object `mxEval` looks inside when evaluating.

### Examples

```
library(OpenMx)

# Set up a 1x1 matrix
matrixA <- mxMatrix("Full", nrow = 1, ncol = 1, values = 1, name = "A")

# Set up an algebra
algebraB <- mxAlgebra(A + A, name = "B")
```

```
# Put them both in a model
testModel <- mxModel(model="testModel", matrixA, algebraB)

# Even though the model has not been run, we can evaluate the algebra
# given the starting values in matrixA.
mxEval(B, testModel, compute=TRUE)

# If we just print the algebra, we can see it has not been evaluated
testModel$B
```

---

mxEvaluateOnGrid	<i>Evaluate an algebra on an abscissa grid and collect column results</i>
------------------	---

---

### Description

This function evaluates an algebra on a grid of points provided in an auxillary abscissa matrix.

### Usage

```
mxEvaluateOnGrid(algebra, abscissa)
```

### Arguments

algebra	the name of the single column matrix to be evaluated.
abscissa	the name of the abscissa matrix. See details.

### Details

The abscissa matrix must be in a specific format. The variables are in the rows. Abscissa row names must match names of free variables. The grid points are in columns. For each point (column), the free variables are set to the given values and the algebra is re-evaluated. The resulting columns are collected as the result.

### Value

Returns the collected columns.

### Examples

```
library(OpenMx)

test2 <- mxModel("test2",
  mxMatrix(values=1.1, nrow=1, ncol=1, free=TRUE, name="thang"),
  mxMatrix(nrow=1, ncol=1, labels="abscissa1", free=TRUE, name="currentAbscissa"),
  mxMatrix(values=-2:2, nrow=1, ncol=5, name="abscissa",
    dimnames=list(c('abscissa1'), NULL)),
```

```
mxAlgebra(rbind(currentAbscissa + thang, currentAbscissa * thang), name="stuff"),
mxAlgebra(mxEvaluateOnGrid(stuff, abscissa), name="grid"))

test2 <- mxRun(test2)
omxCheckCloseEnough(test2$grid$result, matrix(c(-1:3 + .1, -2:2 * 1.1), ncol=5, nrow=2, byrow=TRUE))
```

MxExpectation-class    *MxExpectation*

### Description

This is an internal class and should not be used directly.

mxExpectationBA81    *Create a Bock & Aitkin (1981) expectation*

### Description

Used in conjunction with [mxFitFunctionML](#), this expectation models ordinal data with a modest number of latent dimensions. Currently, only a multivariate Normal latent distribution is supported. An equal-interval quadrature is used to integrate over the latent distribution. When all items use the graded response model and items are assumed conditionally independent then item factor analysis is equivalent to a factor model.

### Usage

```
mxExpectationBA81(ItemSpec, item = "item", ..., qpoints = 49L, qwidth = 6,
  mean = "mean", cov = "cov", verbose = 0L, weightColumn = NA_integer_,
  EstepItem = NULL, debugInternal = FALSE)
```

### Arguments

ItemSpec	a single item model (to replicate) or a list of item models in the same order as the column of ItemParam
item	the name of the mxMatrix holding item parameters with one column for each item model with parameters starting at row 1 and extra rows filled with NA
...	Not used. Forces remaining arguments to be specified by name.
qpoints	number of points to use for equal interval quadrature integration (default 49L)
qwidth	the width of the quadrature as a positive Z score (default 6.0)
mean	the name of the mxMatrix holding the mean vector
cov	the name of the mxMatrix holding the covariance matrix
verbose	the level of runtime diagnostics (default 0L)
weightColumn	the name of the column in the data containing the row weights (DEPRECATED)
EstepItem	a simple matrix of item parameters for the E-step. This option is mainly of use for debugging derivatives.
debugInternal	when enabled, some of the internal tables are returned in \$debug. This is mainly of use to developers.



## Details

The conditional likelihood of response  $x_{ij}$  to item  $j$  from person  $i$  with item parameters  $\xi_j$  and latent ability  $\theta_i$  is

$$L(x_i|\xi, \theta_i) = \prod_j \Pr(\text{pick} = x_{ij}|\xi_j, \theta_i).$$

Items are assumed conditionally independent. That is, the outcome of one item is assumed to not influence another item after controlling for  $\xi$  and  $\theta_i$ . The unconditional likelihood is obtained by integrating over the latent distribution  $\theta_i$ ,

$$L(x_i|\xi) = \int L(x_i|\xi, \theta_i)L(\theta_i)d\theta_i.$$

With an assumption that examinees are independently and identically distributed, we can sum the individual log likelihoods,

$$\mathcal{L} = \sum_i \log L(x_i|\xi).$$

Response models  $\Pr(\text{pick} = x_{ij}|\xi_j, \theta_i)$  are not implemented in OpenMx, but are imported from the [RPF](#) package. You must pass a list of models obtained from the RPF package in the ‘ItemSpec’ argument. All item models must use the same number of latent factors although some of these factor loadings can be constrained to zero in the item parameter matrix. The ‘item’ matrix contains item parameters with one item per column in the same order as ItemSpec.

The ‘qpoints’ and ‘qwidth’ argument control the fineness and width, respectively, of the equal-interval quadrature grid. The integer ‘qpoints’ is the number of points per dimension. The quadrature extends from negative qwidth to positive qwidth for each dimension. Since the latent distribution defaults to standard Normal, qwidth can be regarded as a value in Z-score units.

The optional ‘mean’ and ‘cov’ arguments permit modeling of the latent distribution in multigroup models (in a single group, the latent distribution must be fixed). A separate latent covariance model is used in combination with mxExpectationBA81. The point mass distribution contained in the quadrature is converted into a multivariate Normal distribution by [mxDataDynamic](#). Typically [mxExpectationNormal](#) is used to fit a multivariate Normal model to these data. Some intricate programming is required. Examples are given in the manual. mxExpectationBA81 uses a sample size of  $N$  for the covariance matrix. This differs from [mxExpectationNormal](#) which uses a sample size of  $N - 1$ .

The ‘verbose’ argument enables diagnostics that are mainly of interest to developers.

When a two-tier covariance matrix is recognized, this expectation automatically enables analytic dimension reduction (Cai, 2010).

The optional ‘weightColumn’ is superseded by the weight argument in [mxData](#). For data with many repeated response patterns, model evaluation time can be reduced. An easy way to transform your data into this form is to use [compressDataFrame](#). Non-integer weights are supported except for [EAPscores](#).

mxExpectationBA81 requires [mxComputeEM](#). During a typical optimization run, latent abilities are assumed for examinees during the E-step. These examinee scores are implied by the previous

iteration's parameter vector. This can be overridden using the 'EstepItem' argument. This is mainly of use to developers for checking item parameter derivatives.

Common univariate priors are available from [univariatePrior](#). The standard Normal distribution of the quadrature acts like a prior distribution for difficulty. It is not necessary to impose any additional Bayesian prior on difficulty estimates (Baker & Kim, 2004, p. 196).

Many estimators are available for standard errors. Oakes is recommended (see [mxComputeEM](#)). Also available are Supplement EM ([mxComputeEM](#)), Richardson extrapolation ([mxComputeNumericDeriv](#)), likelihood-based confidence intervals ([mxCI](#)), and the covariance of the rowwise gradients.

## References

Bock, R. D., & Aitkin, M. (1981). Marginal maximum likelihood estimation of item parameters: Application of an EM algorithm. *Psychometrika*, *46*, 443-459.

Cai, L. (2010). A two-tier full-information item factor analysis model with applications. *Psychometrika*, *75*, 581-612.

Pritikin, J. N., Hunter, M. D., & Boker, S. M. (2015). Modular open-source software for Item Factor Analysis. *Educational and Psychological Measurement*, *75*(3), 458-474

Pritikin, J. N. & Schmidt, K. M. (in press). Model builder for Item Factor Analysis with OpenMx. *R Journal*.

Seong, T. J. (1990). Sensitivity of marginal maximum likelihood estimation of item and ability parameters to the characteristics of the prior ability distributions. *Applied Psychological Measurement*, *14*(3), 299-311.

## See Also

[RPF](#)

## Examples

```
library(OpenMx)
library(rpf)

numItems <- 14

# Create item specifications
spec <- list()
for (ix in 1:numItems) { spec[[ix]] <- rpf.grm(outcomes=sample(2:7, 1)) }
names(spec) <- paste("i", 1:numItems, sep="")

# Generate some random "true" parameter values
correct.mat <- mxSimplify2Array(lapply(spec, rpf.rparam))

# Generate some example data
data <- rpf.sample(500, spec, correct.mat)

# Create a matrix of item parameters with starting values
imat <- mxMatrix(name="item",
                 values=mxSimplify2Array(lapply(spec, rpf.rparam)))
```

```

rownames(imat)[1] <- 'f1'
imat$free[!is.na(correct.mat)] <- TRUE
imat$values[!imat$free] <- NA

# Create a compute plan
plan <- mxComputeSequence(list(
  mxComputeEM('expectation', 'scores',
              mxComputeNewtonRaphson(), information="oakes1999",
              infoArgs=list(fitfunction='fitfunction')),
  mxComputeHessianQuality(),
  mxComputeStandardError(),
  mxComputeReportDeriv()))

# Build the OpenMx model
grmModel <- mxModel(model="grm1", imat,
                    mxData(observed=data, type="raw"),
                    mxExpectationBA81(ItemSpec=spec),
                    mxFitFunctionML(),
                    plan)

grmModel <- mxRun(grmModel)
summary(grmModel)

```

---

mxExpectationGREML      *Create MxExpectationGREML Object*

---

## Description

This function creates a new [MxExpectationGREML](#) object.

## Usage

```
mxExpectationGREML(V, yvars=character(0), Xvars=list(), addOnes=TRUE, blockByPheno=TRUE,
                  staggerZeroes=TRUE, dataset.is.yX=FALSE, casesToDropFromV=integer(0))
```

## Arguments

**V**                      Character string; the name of the [MxAlgebra](#) or [MxMatrix](#) to serve as the 'V' matrix (the model-expected covariance matrix). Internally, the 'V' matrix is assumed to be symmetric, and its elements above the main diagonal are ignored.

**yvars, Xvars, addOnes, blockByPheno, staggerZeroes**  
                          Passed to [mxGREMLDataHandler\(\)](#).

**dataset.is.yX**        Logical; defaults to FALSE. If TRUE, then the first column of the raw dataset is taken as-is to be the 'y' phenotype vector, and the remaining columns are taken as-is to be the 'X' matrix of covariates. In this case, [mxGREMLDataHandler\(\)](#) is never internally called at runtime, and all other arguments besides V and casesToDropFromV are ignored.

casesToDropFromV

Integer vector. Its elements are the numbers of the rows and columns of covariance matrix 'V' to be dropped at runtime, usually because they correspond to rows of 'y' or 'X' that contained missing observations. By default, no cases are dropped from 'V.' Ignored unless `dataset.is.yX=TRUE`.

## Details

"GREML" stands for "genomic-relatedness-matrix restricted maximum-likelihood." In the strictest sense of the term, it refers to genetic variance-component estimation from matrices of subjects' pairwise degree of genetic relatedness, as calculated from genome-wide marker data. It is from this original motivation that some of the terminology originates, such as calling 'y' the "phenotype" vector. However, OpenMx's implementation of GREML is applicable for analyses from any subject-matter domain, and in which the following assumptions are reasonable:

1. Conditional on 'X' (the covariates), the phenotype vector (response variable) 'y' is a single realization from a multivariate-normal distribution having (in general) a dense covariance matrix, 'V.'
2. The parameters of the covariance matrix, such as variance components, are of primary interest.
3. The random effects are normally distributed.
4. Weighted least-squares regression, using the inverse of 'V' as a weight matrix, is an adequate model for the phenotypic means. Note that the regression coefficients are not actually free parameters to be numerically optimized.

Computationally, the chief distinguishing feature of an OpenMx GREML analysis is that the phenotype vector, 'y,' is a single realization of a random vector that, in general, cannot be partitioned into independent subvectors. For this reason, definition variables are not compatible (and should be unnecessary with) GREML expectation. GREML expectation can still be used if the covariance matrix is sparse, but as of this writing, OpenMx does not take advantage of the sparseness to improved performance. Because of the limitations of restricted maximum likelihood, GREML expectation is presently incompatible with ordinal variables.

## Value

Returns a new object of class [MxExpectationGREML](#).

## References

One of the first uses of the acronym "GREML":  
 Benjamin DJ, Cesarini D, van der Loos MJHM, Dawes CT, Koellinger PD, et al. (2012) The genetic architecture of economic and political preferences. *Proceedings of the National Academy of Sciences* 109: 8026-8031. doi: 10.1073/pnas.1120666109

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

See [MxExpectationGREML](#) for the S4 class created by `mxExpectationGREML()`. More information about the OpenMx package may be found [here](#).

**Examples**

```

dat <- cbind(rnorm(100),rep(1,100))
colnames(dat) <- c("y","x")

ge <- mxExpectationGREML(V="V",yvars="y",Xvars=list("X"),addOnes=FALSE)
gff <- mxFitFunctionGREML(dV=c("ve","I"))
plan <- mxComputeSequence(freeSet=c("Ve"),steps=list(
  mxComputeNewtonRaphson(fitfunction="fitfunction"),
  mxComputeOnce('fitfunction',
    c('fit','gradient','hessian','ihessian')),
  mxComputeStandardError(),
  mxComputeReportDeriv(),
  mxComputeReportExpectation()
))

testmod <- mxModel(
  "GREMLtest",
  mxData(observed = dat, type="raw"),
  mxMatrix(type = "Full", nrow = 1, ncol=1, free=TRUE,
    values = 1, labels = "ve", lbound = 0.0001, name = "Ve"),
  mxMatrix("Iden",nrow=100,name="I",condenseSlots=TRUE),
  mxAlgebra(I %x% Ve,name="V"),
  ge,
  gff,
  plan
)
str(testmod)

```

---

MxExpectationGREML-class

*Class "MxExpectationGREML"*


---

**Description**

MxExpectationGREML is a type of expectation class. It contains the necessary elements for specifying a GREML model. For more information, see [mxExpectationGREML\(\)](#).

**Objects from the Class**

Objects can be created by calls of the form `mxExpectationGREML(V, yvars, Xvars, addOnes, blockByPheno,`

**Slots**

**V:** Object of class "MxCharOrNumber". Identifies the [MxAlgebra](#) or [MxMatrix](#) to serve as the 'V' matrix.

**yvars:** Character vector. Each string names a column of the raw dataset, to be used as a phenotype.

**Xvars:** A list of data column names, specifying the covariates to be used with each phenotype.

addOnes: Logical; pertains to data-handling at runtime.  
 blockByPheno: Logical; pertains to data-handling at runtime.  
 staggerZeroes: Logical; pertains to data-handling at runtime.  
 dataset.is.yX: Logical; pertains to data-handling at runtime.  
 y: Object of class "MxData". Its observed slot will contain the phenotype vector, 'y.'  
 X: A matrix, to contain the 'X' matrix of covariates.  
 yXcolnames: Character vector; used to store the column names of 'y' and 'X.'  
 casesToDrop: Integer vector, specifying the rows and columns of the 'V' matrix to be removed at runtime.  
 b: A matrix, to contain the vector of regression coefficients calculated at runtime.  
 bcov: A matrix, to contain the sampling covariance matrix of the regression coefficients calculated at runtime.  
 numFixEff: Integer number of covariates in 'X.'  
 dims: Object of class "character".  
 numStats: Numeric; number of observed statistics.  
 dataColumns: Object of class "numeric".  
 name: Object of class "character".  
 data: Object of class "MxCharOrNumber".  
 .runDims: Object of class "character".

### Extends

Class "MxBaseExpectation", directly. Class "MxBaseNamed", by class "MxBaseExpectation", distance 2. Class "MxExpectation", by class "MxBaseExpectation", distance 2.

### Methods

No methods defined with class "MxExpectationGREML" in the signature.

### References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

### See Also

See `mxExpectationGREML()` for creating MxExpectationGREML objects, and for more information generally concerning GREML analyses, including a complete example. More information about the OpenMx package may be found [here](#).

### Examples

```
showClass("MxExpectationGREML")
```

---

 mxExpectationHiddenMarkov

*Hidden Markov expectation*


---

### Description

Used in conjunction with [mxFitFunctionML](#), this expectation can express a mixture model (with the transition matrix omitted) or a Hidden Markov model.

### Usage

```
mxExpectationHiddenMarkov(components, initial="initial", transition=NULL,
  ..., verbose=0L, scale=c('softmax', 'sum', 'none'))
```

### Arguments

components	A character vector of model names.
initial	The name of the matrix or algebra column that specifies the initial probabilities.
transition	The name of the matrix or algebra that specifies the left stochastic transition probabilities.
...	Not used. Forces remaining arguments to be specified by name.
verbose	the level of runtime diagnostics
scale	How the probabilities are rescaled. For 'softmax', the coefficient-wise exponential is taken and then each column is divided by its column sum. For 'sum', each column is divided by its column sum. For 'none', no scaling is done.

### Details

The initial probabilities given in `initial` must sum to one. So too must the *columns* of the transition matrix given in `transition`. The transitions go from a column to a row, similar to how regression effects in the RAM structural equation models go from the column variable to the row variable. This means `transition` is a left stochastic matrix.

For ease of use the raw free parameters of these matrices are rescaled by OpenMx according to the `scale` argument. When `scale` is set to "softmax" the softmax function is applied to the initial probabilities and the columns of the transition matrix. The softmax function is also sometimes called multinomial logistic regression. Softmax exponentiates each element in a vector and then divides each element by the sum of the exponentiated elements. In equation form the softmax function is

$$\text{softmax}(x_i) = \frac{e^{x_i}}{\sum_{k=1}^K e^{x_k}}$$

When using the softmax scaling no free parameter bounds or constraints are needed. However, for model identification, one element of the initial probabilities vector must be fixed. If the softmax scaling is used, then the usual choice for the fixed parameter value is zero. The regime (or latent

class or mixture component) that has its initial probability set to zero becomes the comparison against which other probabilities are evaluated. Likewise for model identification, one element in each column of the transition matrix must be fixed. When the softmax scaling is used, the typical choice is to fix one element in each column to zero. Generally, one row of the transition matrix is fixed to zero, or the diagonal elements of the transition matrix are fixed to zero.

When scale is set to "sum" then each element of the initial probabilities and each column of the transition matrix is internally divided by its sum. When using the sum scaling, the same model identification requirements are present. In particular, one element of the initial probabilities must be fixed and one element in each column of the transition matrix must be fixed. The typical value to fix these values at for sum scaling is one. Additionally when using sum scaling, all free parameters in the initial and transition probabilities must have lower bounds of zero. In equation form the sum scaling does the following:

$$sumscale(x_i) = \frac{x_i}{\sum_{k=1}^K x_k}$$

When scale is set to "none" then no re-scaling is done. The parameters of initial and transition are left "as is". This can be dangerous and is not recommended for novice users. It might produce nonsensical results particularly for hidden Markov models. However, some advanced users may find no scaling to be advantageous for certain applications (e.g., they are providing their own scaling), and thus it is provided as an option.

Parameters are estimated in the given scale. To obtain the initial column vector and left stochastic transition matrix in probability units then examine the expectation's output slot with for example `yourModel$expectation$output`

Definition variables can be used to assign a separate set of mixture probabilities to each row of data. Definition variables can be used in the initial column vector or in the transition matrix, but not in both at the same time.

Note that, when the transition matrix is omitted, this expectation is the same as [mxExpectationMixture](#). [mxGenerateData](#) is not implemented for this type of expectation.

## Examples

```
library(OpenMx)

start_prob <- c(.2,.4,.4)
transition_prob <- matrix(c(.8, .1, .1,
.3, .6, .1,
.1, .3, .6), 3, 3)
noise <- .5

# simulate a trajectory
state <- sample.int(3, 1, prob=transition_prob %*% start_prob)
trail <- c(state)

for (rep in 1:500) {
  state <- sample.int(3, 1, prob=transition_prob[,state])
  trail <- c(trail, state)
}
```



```

# add noise
trailN <- sapply(trail, function(v) rnorm(1, mean=v, sd=sqrt(noise)))

classes <- list()

for (cl in 1:3) {
  classes[[cl]] <- mxModel(paste0("cl", cl), type="RAM",
    manifestVars=c("ob"),
    mxPath("one", "ob", value=cl, free=FALSE),
    mxPath("ob", arrows=2, value=noise, free=FALSE),
    mxFitFunctionML(vector=TRUE))
}

m1 <-
  mxModel("hmm", classes,
    mxData(data.frame(ob=trailN), "raw"),
    mxMatrix(nrow=3, ncol=1,
      labels=paste0('i',1:3), name="initial"),
    mxMatrix(nrow=length(classes), ncol=length(classes),
      labels=paste0('t', 1:(length(classes) * length(classes))),
      name="transition"),
    mxExpectationHiddenMarkov(
      components=sapply(classes, function(m) m$name),
      initial="initial",
      transition="transition", scale="softmax"),
    mxFitFunctionML())

  m1$transition$free[1:(length(classes)-1), 1:length(classes)] <- TRUE

m1 <- mxRun(m1)

summary(m1)

print(m1$expectation$output)

```

---

mxExpectationLISREL     *Create MxExpectationLISREL Object*

---

## Description

This function creates a new MxExpectationLISREL object.

## Usage

```

mxExpectationLISREL(LX=NA, LY=NA, BE=NA, GA=NA, PH=NA, PS=NA, TD=NA, TE=NA, TH=NA,
  TX = NA, TY = NA, KA = NA, AL = NA,
  dimnames = NA, thresholds = NA, threshnames = dimnames)

```

### Arguments

LX	An optional character string indicating the name of the 'LX' matrix.
LY	An optional character string indicating the name of the 'LY' matrix.
BE	An optional character string indicating the name of the 'BE' matrix.
GA	An optional character string indicating the name of the 'GA' matrix.
PH	An optional character string indicating the name of the 'PH' matrix.
PS	An optional character string indicating the name of the 'PS' matrix.
TD	An optional character string indicating the name of the 'TD' matrix.
TE	An optional character string indicating the name of the 'TE' matrix.
TH	An optional character string indicating the name of the 'TH' matrix.
TX	An optional character string indicating the name of the 'TX' matrix.
TY	An optional character string indicating the name of the 'TY' matrix.
KA	An optional character string indicating the name of the 'KA' matrix.
AL	An optional character string indicating the name of the 'AL' matrix.
dimnames	An optional character vector that is currently ignored
thresholds	An optional character string indicating the name of the thresholds matrix.
threshnames	An optional character vector to be assigned to the column names of the thresholds matrix.

### Details

Expectation functions define the way that model expectations are calculated. The mxExpectation-LISREL calculates the expected covariance and means of a given `MxData` object given a LISREL model. This model is defined by Linear Structural Relations (LISREL; Jöreskog & Sörbom, 1982, 1996). Arguments 'LX' through 'AL' must refer to `MxMatrix` objects with the associated properties of their respective matrices in the LISREL modeling approach.

The full LISREL specification has 13 matrices and is sometimes called the extended LISREL model. It is defined by the following equations.

$$\eta = \alpha + B\eta + \Gamma\xi + \zeta$$

$$y = \tau_y + \Lambda_y\eta + \epsilon$$

$$x = \tau_x + \Lambda_x\xi + \delta$$

The table below is provided as a quick reference to the numerous matrices in LISREL models. Note that NX is the number of manifest exogenous (independent) variables, the number of Xs. NY is the number of manifest endogenous (dependent) variables, the number of Ys. NK is the number of latent exogenous variables, the number of Ksis or Xis. NE is the number of latent endogenous variables, the number of etas.

Matrix	Word	Abbreviation	Dimensions	Expression	Description
$\Lambda_x$	Lambda x	LX	NX x NK		Exogenous Factor Loading Matrix
$\Lambda_y$	Lambda y	LY	NY x NE		Endogenous Factor Loading Matrix

$B$	Beta	BE	NE x NE		Regressions of Latent Endogenous Variables Pred
$\Gamma$	Gamma	GA	NE x NK		Regressions of Latent Exogenous Variables Pred
$\Phi$	Phi	PH	NK x NK	cov( $\xi$ )	Covariance Matrix of Latent Exogenous Variable
$\Psi$	Psi	PS	NE x NE	cov( $\zeta$ )	Residual Covariance Matrix of Latent Endogeno
$\Theta_\delta$	Theta delta	TD	NX x NX	cov( $\delta$ )	Residual Covariance Matrix of Manifest Exogeno
$\Theta_\epsilon$	Theta epsilon	TE	NY x NY	cov( $\epsilon$ )	Residual Covariance Matrix of Manifest Endogeno
$\Theta_{\delta\epsilon}$	Theta delta epsilon	TH	NX x NY	cov( $\delta, \epsilon$ )	Residual Covariance Matrix of Manifest Exogeno
$\tau_x$	tau x	TX	NX x 1		Residual Means of Manifest Exogenous Variable
$\tau_y$	tau y	TY	NY x 1		Residual Means of Manifest Endogenous Variabl
$\kappa$	kappa	KA	NK x 1	mean( $\xi$ )	Means of Latent Exogenous Variables
$\alpha$	alpha	AL	NE x 1		Residual Means of Latent Endogenous Variables

From the extended LISREL model, several submodels can be defined. Subtypes of the LISREL model are defined by setting some of the arguments of the LISREL expectation function to NA. Note that because the default values of each LISREL matrix is NA, setting a matrix to NA can be accomplished by simply not giving it any other value.

The first submodel is the LISREL model without means.

$$\eta = B\eta + \Gamma\xi + \zeta$$

$$y = \Lambda_y\eta + \epsilon$$

$$x = \Lambda_x\xi + \delta$$

The LISREL model without means requires 9 matrices: LX, LY, BE, GA, PH, PS, TD, TE, and TH. Hence this LISREL model has TX, TY, KA, and AL as NA. This can be accomplished by leaving these matrices at their default values.

The TX, TY, KA, and AL matrices must be specified if either the mxData type is “cov” or “cor” and a means vector is provided, or if the mxData type is “raw”. Otherwise the TX, TY, KA, and AL matrices are ignored and the model without means is estimated.

A second submodel involves only endogenous variables.

$$\eta = B\eta + \zeta$$

$$y = \Lambda_y\eta + \epsilon$$

The endogenous-only LISREL model requires 4 matrices: LY, BE, PS, and TE. The LX, GA, PH, TD, and TH must be NA in this case. However, means can also be specified, allowing TY and AL if the data are raw or if observed means are provided.

Another submodel involves only exogenous variables.

$$x = \Lambda_x\xi + \delta$$

The exogenous-only LISREL model requires 3 matrices: LX, PH, and TD. The LY, BE, GA, PS, TE, and TH matrices must be NA. However, means can also be specified, allowing TX and KA if the data are raw or if observed means are provided.

The model that is run depends on the matrices that are not NA. If all 9 matrices are not NA, then the full model is run. If only the 4 endogenous matrices are not NA, then the endogenous-only model is run. If only the 3 exogenous matrices are not NA, then the exogenous-only model is run. If some endogenous and exogenous matrices are not NA, but not all of them, then appropriate errors are thrown. Means are included in the model whenever their matrices are provided.

The `MxMatrix` objects included as arguments may be of any type, but should have the properties described above. The `mxExpectationLISREL` will not return an error for incorrect specification, but incorrect specification will likely lead to estimation problems or errors in the `mxRun` function.

Like the `mxExpectationRAM`, the `mxExpectationLISREL` evaluates with respect to an `MxData` object. The `MxData` object need not be referenced in the `mxExpectationLISREL` function, but must be included in the `MxModel` object. `mxExpectationLISREL` requires that the 'type' argument in the associated `MxData` object be equal to 'cov', 'cor', or 'raw'.

To evaluate, place `mxExpectationLISREL` objects, the `MxData` object for which the expected covariance approximates, referenced `MxAlgebra` and `MxMatrix` objects, and optional `MxBounds` and `MxConstraint` objects in an `MxModel` object. This model may then be evaluated using the `mxRun` function. The results of the optimization can be found in the 'output' slot of the resulting model, and may be obtained using the `mxEval` function.

### Value

Returns a new `MxExpectationLISREL` object. One and only one `MxExpectationLISREL` object can be included with models using one and only one fit function object (e.g., `MxFitFunctionML`) and with referenced `MxAlgebra`, `MxData` and `MxMatrix` objects.

### References

Jöreskog, K. G. & Sörbom, D. (1996). *LISREL 8: User's Reference Guide*. Lincolnwood, IL: Scientific Software International.

Jöreskog, K. G. & Sörbom, D. (1982). Recent developments in structural equation modeling. *Journal of Marketing Research*, 19, 404-416.

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

### See Also

`demo("LISRELJointFactorModel")`

### Examples

```
# Create and fit a model using mxExpectationLISREL, and mxFitFunctionML

library(OpenMx)

vNames <- paste("v", as.character(1:6), sep="")
dimList <- list(vNames, vNames)
covData <- matrix(
  c(0.9223099, 0.1862938, 0.4374359, 0.8959973, 0.9928430, 0.5320662,
    0.1862938, 0.2889364, 0.3927790, 0.3321639, 0.3371594, 0.4476898,
    0.4374359, 0.3927790, 1.0069552, 0.6918755, 0.7482155, 0.9013952,
```

```

0.8959973, 0.3321639, 0.6918755, 1.8059956, 1.6142005, 0.8040448,
0.9928430, 0.3371594, 0.7482155, 1.6142005, 1.9223567, 0.8777786,
0.5320662, 0.4476898, 0.9013952, 0.8040448, 0.8777786, 1.3997558
), nrow=6, ncol=6, byrow=TRUE, dimnames=dimList)

# Create LISREL matrices

mLX <- mxMatrix("Full", values=c(.5, .6, .8, rep(0, 6), .4, .7, .5),
  name="LX", nrow=6, ncol=2,
  free=c(TRUE,TRUE,TRUE,rep(FALSE, 6),TRUE,TRUE,TRUE),
  dimnames=list(vNames, c("x1","x2")))
mTD <- mxMatrix("Diag", values=c(rep(.2, 6)),
  name="TD", nrow=6, ncol=6, free=TRUE,
  dimnames=dimList)
mPH <- mxMatrix("Symm", values=c(1, .3, 1),
  name="PH", nrow=2, ncol=2, free=c(FALSE, TRUE, FALSE),
  dimnames=list(c("x1","x2"),c("x1","x2")))

# Create a LISREL expectation with LX, TD, and PH matrix names

expFunction <- mxExpectationLISREL(LX="LX", TD="TD", PH="PH")

# Create fit function and data

tmpData <- mxData(observed=covData, type="cov", numObs=100)
fitFunction <- mxFitFunctionML()

# Create the model, fit it, and print a summary.

tmpModel <- mxModel(model="exampleModel",
  mLX, mTD, mPH, expFunction, fitFunction, tmpData)
tmpModelOut <- mxRun(tmpModel)
summary(tmpModelOut)

#-----
# Fit factor model with means

require(OpenMx)

data(demoOneFactor)
nvar <- ncol(demoOneFactor)
varnames <- colnames(demoOneFactor)

factorMeans <- mxMatrix("Zero", 1, 1, name="Kappa",
  dimnames=list("F1", NA))
xIntercepts <- mxMatrix("Full", nvar, 1, free=TRUE, name="TauX",
  dimnames=list(varnames, NA))
factorLoadings <- mxMatrix("Full", nvar, 1, TRUE, .6, name="LambdaX",
  labels=paste("lambda", 1:nvar, sep=""),
  dimnames=list(varnames, "F1"))
factorCovariance <- mxMatrix("Diag", 1, 1, FALSE, 1, name="Phi")
xResidualVariance <- mxMatrix("Diag", nvar, nvar, TRUE, .2, name="ThetaDelta",

```

```

labels=paste("theta", 1:nvar, sep=""))

liModel <- mxModel(model="LISREL Factor Model",
  factorMeans, xIntercepts, factorLoadings,
  factorCovariance, xResidualVariance,
  mxExpectationLISREL(LX="LambdaX", PH="Phi",
    TD="ThetaDelta", TX="TauX", KA="Kappa"),
  mxFitFunctionML(),
  mxData(cov(demoOneFactor), "cov",
  means=colMeans(demoOneFactor), numObs=nrow(demoOneFactor))
)

liRun <- mxRun(liModel)

summary(liRun)

```

---

mxExpectationMixture    *Mixture expectation*

---

## Description

Used in conjunction with [mxFitFunctionML](#), this expectation can express a mixture model.

## Usage

```

mxExpectationMixture(components, weights="weights",
  ..., verbose=0L, scale=c('softmax', 'sum', 'none'))

```

## Arguments

components	A character vector of model names.
weights	The name of the matrix or algebra column that specifies the component weights.
...	Not used. Forces remaining arguments to be specified by name.
verbose	the level of runtime diagnostics
scale	How the probabilities are rescaled. For 'softmax', the coefficient-wise exponential is taken and then each column is divided by its column sum. For 'sum', each column is divided by its column sum. For 'none', no scaling is done.

## Details

The mixture probabilities given in `weights` must sum to one. As such for  $K$  mixture components, only  $K - 1$  of the elements of `weights` can be estimated. The mixture probabilities in `weights` should be a column vector (i.e., a  $K$  by 1 matrix, or algebra with a  $K$  by 1 result).

For ease of use the raw free parameters of `weights` can be rescaled by OpenMx according to the `scale` argument. When `scale` is set to "softmax" the softmax function is applied to the weights. The softmax function is also sometimes called multinomial logistic regression. Softmax exponentiates each element in a vector and then divides each element by the sum of the exponentiated elements. In equation form the softmax function is

$$\text{softmax}(x_i) = \frac{e^{x_i}}{\sum_{k=1}^K e^{x_k}}$$

When using the softmax scaling no free parameter bounds or constraints are needed. However, for model identification, one element of the weights vector must be fixed. If the softmax scaling is used, then the usual choice for the fixed parameter value is zero. The latent class or mixture component that has its raw weight set to zero becomes the comparison against which other probabilities are evaluated.

When scale is set to "sum" then each element of the weights matrix is internally divided by its sum. When using the sum scaling, the same model identification requirements are present. In particular, one element of the weights must be fixed. The typical value to fix this value at for sum scaling is one. Additionally when using sum scaling, all free parameters in the weights must have lower bounds of zero. In equation form the sum scaling does the following:

$$\text{sum.scale}(x_i) = \frac{x_i}{\sum_{k=1}^K x_k}$$

When scale is set to "none" then no re-scaling is done. The weights are left "as is". This can be dangerous and is not recommended for novice users. However, some advanced users may find no scaling to be advantageous for certain applications (e.g., they are providing their own scaling), and thus it is provided as an option.

Parameters are estimated in the given scale. To obtain the weights column vector, examine the expectation's output slot with for example `yourModel$expectation$output`

An extension of this expectation to a Hidden Markov model is available with [mxExpectationHiddenMarkov](#). [mxGenerateData](#) is not implemented for this type of expectation.

## Examples

```
library(OpenMx)

set.seed(1)

trail <- c(rep(1,480), rep(2,520))
trailN <- sapply(trail, function(v) rnorm(1, mean=v))

classes <- list()

for (cl in 1:2) {
  classes[[cl]] <- mxModel(paste0("class", cl), type="RAM",
    manifestVars=c("ob"),
    mxPath("one", "ob", value=cl, free=FALSE),
    mxPath("ob", arrows=2, value=1, free=FALSE),
    mxFitFunctionML(vector=TRUE))
}

mix1 <- mxModel(
  "mix1", classes,
  mxData(data.frame(ob=trailN), "raw"),
```

```

mxMatrix(values=1, nrow=1, ncol=2, free=c(FALSE,TRUE), name="weights"),
mxExpectationMixture(paste0("class",1:2), scale="softmax"),
mxFitFunctionML())

mix1Fit <- mxRun(mix1)

```

---

mxExpectationNormal     *Create MxExpectationNormal Object*

---

## Description

This function creates an MxExpectationNormal object.

## Usage

```

mxExpectationNormal(covariance, means, dimnames = NA, thresholds = NA,
                    threshnames = dimnames)

```

## Arguments

covariance	A character string indicating the name of the expected covariance algebra.
means	A character string indicating the name of the expected means algebra.
dimnames	An optional character vector to be assigned to the dimnames of the covariance and means algebras.
thresholds	An optional character string indicating the name of the thresholds matrix.
threshnames	An optional character vector to be assigned to the column names of the thresholds matrix.

## Details

Expectation functions define the way that model expectations are calculated. The mxExpectationNormal function uses the algebra defined by the 'covariance' and 'means' arguments to define the expected covariance and means under the assumption of multivariate normality. The 'covariance' argument takes an [MxAlgebra](#) object, which defines the expected covariance of an associated [MxData](#) object. The 'means' argument takes an [MxAlgebra](#) object, which defines the expected means of an associated [MxData](#) object. The 'dimnames' arguments takes an optional character vector. If this argument is not a single NA, then this vector is used to assign the dimnames of the means vector as well as the row and columns dimnames of the covariance matrix.

**thresholds:** The name of the thresholds matrix. When needed (for modelling ordinal data), this matrix should be created using [mxMatrix\(\)](#). The thresholds matrix must have as many columns as there are ordinal variables in the model, and number of rows equal to one fewer than the maximum number of levels found in the ordinal variables. The starting values of this matrix must also be set to reasonable values. Fill each column with a set of ordered start thresholds, one for each level of this column's factor levels minus 1. These thresholds may be free if you wish them to be estimated, or fixed. The unused rows in each column, if any, can be set to any value including NA.



threshnames: A character vector consisting of the variables in the thresholds matrix, i.e., the names of ordinal variables in a model. This is necessary for OpenMx to map the thresholds matrix columns onto the variables in your data. If you set the `dimnames` of the columns in the thresholds matrix then `threshnames` is not needed.

Usage Notes: `dimnames` must be supplied where the matrices referenced by the covariance and means algebras are not themselves labeled. Failure to do so leads to an error noting that the covariance or means matrix associated with the FIML objective does not contain `dimnames`.

`mxExpectationNormal` evaluates with respect to an `MxData` object. The `MxData` object need not be referenced in the `mxExpectationNormal` function, but must be included in the `MxModel` object. When the 'type' argument in the associated `MxData` object is equal to 'raw', missing values are permitted in the associated `MxData` object.

To evaluate, place an `mxExpectationNormal` object, the `mxData` object for which the expected covariance approximates, referenced `MxAlgebra` and `MxMatrix` objects, optional `MxBounds` or `MxConstraint` objects, and an `mxFitFunction` such as `mxFitFunctionML` in an `MxModel` object. This model may then be evaluated using the `mxRun` function.

The results of the optimization can be reported using the `summary` function, or accessed directly in the 'output' slot of the resulting model (i.e., `modelName$output`). Components of the output may be referenced using the `Extract` functionality.

## Value

Returns an `MxExpectationNormal` object.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## Examples

```
# Create and fit a model using mxMatrix, mxAlgebra,
# mxExpectationNormal, and mxFitFunctionML

library(OpenMx)

# Simulate some data

x=rnorm(1000, mean=0, sd=1)
y= 0.5*x + rnorm(1000, mean=0, sd=1)
tmpFrame <- data.frame(x, y)
tmpNames <- names(tmpFrame)

# Define the matrices

M <- mxMatrix(type = "Full", nrow = 1, ncol = 2, values=c(0,0),
              free=c(TRUE,TRUE), labels=c("Mx", "My"), name = "M")
S <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(1,0,0,1),
              free=c(TRUE,FALSE,FALSE,TRUE), labels=c("Vx", NA, NA, "Vy"),
              name = "S")
A <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(0,1,0,0),
```

```

        free=c(FALSE,TRUE,FALSE,FALSE), labels=c(NA, "b", NA, NA),
        name = "A")
I <- mxMatrix(type="Iden", nrow=2, ncol=2, name="I")

# Define the expectation

expCov <- mxAlgebra(solve(I-A) %*% S %*% t(solve(I-A)), name="expCov")
expFunction <- mxExpectationNormal(covariance="expCov", means="M",
dimnames=tmpNames)

# Choose a fit function

fitFunction <- mxFitFunctionML()

# Define the model

tmpModel <- mxModel(model="exampleModel", M, S, A, I,
                    expCov, expFunction, fitFunction,
                    mxData(observed=tmpFrame, type="raw"))

# Fit the model and print a summary

tmpModelOut <- mxRun(tmpModel)
summary(tmpModelOut)

```

---

mxExpectationRAM

*Create an MxExpectationRAM Object*


---

## Description

This function creates an MxExpectationRAM object.

## Usage

```
mxExpectationRAM(A="A", S="S", F="F", M = NA, dimnames = NA, thresholds = NA,
                 threshnames = dimnames, ..., between=NULL, verbose=0L)
```

## Arguments

A	A character string indicating the name of the 'A' matrix.
S	A character string indicating the name of the 'S' matrix.
F	A character string indicating the name of the 'F' matrix.
M	An optional character string indicating the name of the 'M' matrix.
dimnames	An optional character vector to be assigned to the column names of the 'F' and 'M' matrices.
thresholds	An optional character string indicating the name of the thresholds matrix.

threshnames	An optional character vector to be assigned to the column names of the thresholds matrix.
...	Not used. Forces remaining arguments to be specified by name.
between	A character vector of matrices that specify cross model relationships.
verbose	integer. Level of runtime diagnostic output.

## Details

Expectation functions define the way that model expectations are calculated. The `mxExpectationRAM` calculates the expected covariance and means of a given `MxData` object given a RAM model. This model is defined by reticular action modeling (McArdle and McDonald, 1984). The 'A', 'S', and 'F' arguments must refer to `MxMatrix` objects with the associated properties of the A, S, and F matrices in the RAM modeling approach.

The 'dimnames' argument takes an optional character vector. If this argument is not a single NA, then this vector be assigned to be the column names of the 'F' matrix and optionally to the 'M' matrix, if the 'M' matrix exists.

The 'A' argument refers to the A or asymmetric matrix in the RAM approach. This matrix consists of all of the asymmetric paths (one-headed arrows) in the model. A free parameter in any row and column describes a regression of the variable represented by that row regressed on the variable represented in that column.

The 'S' argument refers to the S or symmetric matrix in the RAM approach, and as such must be square. This matrix consists of all of the symmetric paths (two-headed arrows) in the model. A free parameter in any row and column describes a covariance between the variable represented by that row and the variable represented by that column. Variances are covariances between any variable at itself, which occur on the diagonal of the specified matrix.

The 'F' argument refers to the F or filter matrix in the RAM approach. If no latent variables are included in the model (i.e., the A and S matrices are of both of the same dimension as the data matrix), then the 'F' should refer to an identity matrix. If latent variables are included (i.e., the A and S matrices are not of the same dimension as the data matrix), then the 'F' argument should consist of a horizontal adhesion of an identity matrix and a matrix of zeros.

The 'M' argument refers to the M or means matrix in the RAM approach. It is a 1 x n matrix, where n is the number of manifest variables + the number of latent variables. The M matrix must be specified if either the `mxData` type is "cov" or "cor" and a means vector is provided, or if the `mxData` type is "raw". Otherwise the M matrix is ignored.

The `MxMatrix` objects included as arguments may be of any type, but should have the properties described above. The `mxExpectationRAM` will not return an error for incorrect specification, but incorrect specification will likely lead to estimation problems or errors in the `mxRun` function.

`mxExpectationRAM` evaluates with respect to an `MxData` object. The `MxData` object need not be referenced in the `mxExpectationRAM` function, but must be included in the `MxModel` object.

To evaluate, place `mxExpectationRAM` objects, the `mxData` object for which the expected covariance approximates, referenced `MxAlgebra` and `MxMatrix` objects, and optional `MxBounds` and `MxConstraint` objects in an `MxModel` object. This model may then be evaluated using the `mxRun` function. The results of the optimization can be found in the 'output' slot of the resulting model, and may be obtained using the `mxEval` function..

**Value**

Returns a new MxExpectationRAM object. mxExpectationRAM objects should be included with models with referenced [MxAlgebra](#), [MxData](#) and [MxMatrix](#) objects.

**References**

McArdle, J. J. and MacDonald, R. P. (1984). Some algebraic properties of the Reticular Action Model for moment structures. *British Journal of Mathematical and Statistical Psychology*, 37, 234-251.

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
# Create and fit a model using mxMatrix, mxAlgebra,
# mxExpectationNormal, and mxFitFunctionML

library(OpenMx)

# Simulate some data

x=rnorm(1000, mean=0, sd=1)
y= 0.5*x + rnorm(1000, mean=0, sd=1)
tmpFrame <- data.frame(x, y)
tmpNames <- names(tmpFrame)

# Define the matrices

matrixS <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(1,0,0,1),
                    free=c(TRUE,FALSE,FALSE,TRUE), labels=c("Vx", NA, NA, "Vy"),
                    name = "S")
matrixA <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(0,1,0,0),
                    free=c(FALSE,TRUE,FALSE,FALSE), labels=c(NA, "b", NA, NA),
                    name = "A")
matrixF <- mxMatrix(type="Iden", nrow=2, ncol=2, name="F")
matrixM <- mxMatrix(type = "Full", nrow = 1, ncol = 2, values=c(0,0),
                    free=c(TRUE,TRUE), labels=c("Mx", "My"), name = "M")

# Define the expectation

expFunction <- mxExpectationRAM(M="M", dimnames = tmpNames)

# Choose a fit function

fitFunction <- mxFitFunctionML()

# Define the model

tmpModel <- mxModel(model="exampleRAMModel",
                    matrixA, matrixS, matrixF, matrixM,
                    expFunction, fitFunction,
```

```

mxData(observed=tmpFrame, type="raw"))

# Fit the model and print a summary

tmpModelOut <- mxRun(tmpModel)
summary(tmpModelOut)

```

---

mxExpectationStateSpace

*Create an MxExpectationStateSpace Object*

---

## Description

This function creates a new MxExpectationStateSpace object.

## Usage

```

mxExpectationStateSpace(A, B, C, D, Q, R, x0, P0, u,
                        dimnames = NA, thresholds = NA, threshnames = dimnames,
                        ..., t = NA, scores=FALSE)

```

## Arguments

A	A character string indicating the name of the 'A' matrix.
B	A character string indicating the name of the 'B' matrix.
C	A character string indicating the name of the 'C' matrix.
D	A character string indicating the name of the 'D' matrix.
Q	A character string indicating the name of the 'Q' matrix.
R	A character string indicating the name of the 'R' matrix.
x0	A character string indicating the name of the 'x0' matrix.
P0	A character string indicating the name of the 'P0' matrix.
u	A character string indicating the name of the 'u' matrix.
dimnames	An optional character vector to be assigned to the row names of the 'C' matrix.
thresholds	Not Yet Implemented. An optional character string indicating the name of the thresholds matrix.
threshnames	Not Yet Implemented. An optional character vector to be assigned to the column names of the thresholds matrix.
...	Unused. Requires further arguments to be named.
t	Not to be used
scores	Not to be used

## Details

Expectation functions define the way that model expectations are calculated. When used in conjunction with the [mxFitFunctionML](#), the `mxExpectationStateSpace` uses maximum likelihood prediction error decomposition (PED) to obtain estimates of free parameters in a model of the raw `MxData` object. State space expectations treat the raw data as a multivariate time series of equally spaced times with each row corresponding to a single occasion. This is not a model of the block Toeplitz lagged autocovariance matrix. State space expectations implement a classical Kalman filter to produce expectations.

The hybrid Kalman filter (combination of classical Kalman and Kalman-Bucy filters) for continuous latent time with discrete observations is implemented and is available as [mxExpectationStateSpace-ContinuousTime](#). The following alternative filters are not yet implemented: square root Kalman filter (in Cholesky or singular value decomposition form), extended Kalman filter for linear approximations to nonlinear state space models, unscented Kalman filter for highly nonlinear state space models, and Rauch-Tung-Striebel smoother for updating forecast state estimates after a complete forward pass through the data has been made.

Missing data handling is implemented in the same fashion as full information maximum likelihood for partially missing rows of data. Additionally, completely missing rows of data are handled by only using the prediction step from the Kalman filter and omitting the update step.

This model uses notation for the model matrices commonly found in engineering and control theory. The 'A', 'B', 'C', 'D', 'Q', 'R', 'x0', and 'P0' arguments must be the names of [MxMatrix](#) or [MxAlgebra](#) objects with the associated properties of the A, B, C, D, Q, R, x0, and P0 matrices in the state space modeling approach.

The state space expectation is defined by the following model equations.

$$x_t = Ax_{t-1} + Bu_t + q_t$$

$$y_t = Cx_t + Du_t + r_t$$

with  $q_t$  and  $r_t$  both independently and identically distributed random Gaussian (normal) variables with mean zero and covariance matrices  $Q$  and  $R$ , respectively.

The first equation is called the state equation. It describes how the latent states change over time. Also, the state equation in state space modeling is directly analogous to the structural model in LISREL structural equation modeling.

The second equation is called the output equation. It describes how the latent states relate to the observed states at a single point in time. The output equation shows how the observed output is produced by the latent states. Also, the output equation in state space modeling is directly analogous to the measurement model in LISREL structural equation modeling.

Note that the covariates,  $u$ , have "instantaneous" effects on both the state and output equations. If lagged effects are desired, then the user must create a lagged covariate by shifting their observed variable to the desired lag.

The state and output equations, together with some minimal assumptions and the Kalman filter, imply a new expected covariance matrix and means vector for every row of data. The expected covariance matrix of row  $t$  is

$$S_t = C(AP_{t-1}A^T + Q)C^T + R$$

The expected means vector of row  $t$  is

$$\hat{y}_t = Cx_t + Du_t$$

The 'dimnames' argument takes an optional character vector.

The 'A' argument refers to the  $A$  matrix in the State Space approach. This matrix consists of time regressive coefficients from the latent variable in column  $j$  at time  $t - 1$  to the latent variable in row  $i$  at time  $t$ . Entries in the diagonal are autoregressive coefficients. Entries in the off-diagonal are cross-lagged regressive coefficients. If the  $A$  and  $B$  matrices are zero matrices, then the state space model reduces to a factor analysis. The  $A$  matrix is sometimes called the state-transition model.

The 'B' argument refers to the  $B$  matrix in the State Space approach. This matrix consists of regressive coefficients from the input (manifest covariate) variable  $j$  at time  $t$  to the latent variable in row  $i$  at time  $t$ . Note that the covariate effect is contemporaneous: the covariate at time  $t$  has influence on the latent state also at time  $t$ . A lagged effect can be created by lagged the observed variable. The  $B$  matrix is sometimes called the control-input model.

The 'C' argument refers to the  $C$  matrix in the State Space approach. This matrix consists of contemporaneous regression coefficients from the latent variable in column  $j$  to the observed variable in row  $i$ . This matrix is directly analogous to the factor loadings matrix in LISREL and Mplus models. The  $C$  matrix is sometimes called the observation model.

The 'D' argument refers to the  $D$  matrix in the State Space approach. This matrix consists of contemporaneous regressive coefficients from the input (manifest covariate) variable  $j$  to the observed variable in row  $i$ . The  $D$  matrix is sometimes called the feedthrough or feedforward matrix.

The 'Q' argument refers to the  $Q$  matrix in the State Space approach. This matrix consists of residual covariances among the latent variables. This matrix must be symmetric. As a special case, it is often diagonal. The  $Q$  matrix is the covariance of the process noise. Just as in factor analysis and general structural equation modeling, the scale of the latent variables is usually set by fixing some factor loadings in the  $C$  matrix, or fixing some factor variances in the  $Q$  matrix.

The 'R' argument refers to the  $R$  matrix in the State Space approach. This matrix consists of residual covariances among the observed (manifest) variables. This matrix must be symmetric. As a special case, it is often diagonal. The  $R$  matrix is the covariance of the observation noise.

The 'x0' argument refers to the  $x_0$  matrix in the State Space approach. This matrix consists of the column vector of the initial values for the latent variables. The state space expectation uses the  $x_0$  matrix as the starting point to recursively estimate the latent variables' values at each time. These starting values can be difficult to pick, however, for sufficiently long time series they often do not greatly impact the estimation.

The 'P0' argument refers to the  $P_0$  matrix in the State Space approach. This matrix consists of the initial values of the covariances of the error in the initial latent variable estimates given in  $x_0$ . That is, the  $P_0$  matrix gives the covariance of  $x_0 - x_{true_0}$  where  $x_{true_0}$  is the vector of true initial values.  $P_0$  is a measure of the accuracy of the initial latent state estimates. The Kalman filter uses this initial covariance to recursively generated a new covariance for each time point based on the previous time point. The Kalman filter updates this covariance so that it is as small as possible (minimum trace). Similar to the  $x_0$  matrix, these starting values are often difficult to choose.

The 'u' argument refers to the  $u$  matrix in the State Space approach. This matrix consists of the inputs or manifest covariates of the state space expectation. The  $u$  matrix must be a column vector with the same number of rows as the  $B$  and  $D$  matrices have columns. If no inputs are desired,  $u$

can be a zero matrix. If time-varying inputs are desired, then they should be included as columns in the `MxData` object and referred to in the labels of the  $u$  matrix as definition variables. There is an example of this below.

The `MxMatrix` objects included as arguments may be of any type, but should have the properties described above. The `mxExpectationStateSpace` will not return an error for incorrect specification, but incorrect specification will likely lead to estimation problems or errors in the `mxRun` function.

`mxExpectationStateSpace` evaluates with respect to an `MxData` object. The `MxData` object need not be referenced in the `mxExpectationStateSpace` function, but must be included in the `MxModel` object. `mxExpectationStateSpace` requires that the 'type' argument in the associated `MxData` object be equal to 'raw'. Neighboring rows of the `MxData` object are treated as adjacent, equidistant time points increasing from the first to the last row.

To evaluate, place `mxExpectationStateSpace` objects, the `mxData` object for which the expected covariance approximates, referenced `MxAlgebra` and `MxMatrix` objects, and optional `MxBounds` and `MxConstraint` objects in an `MxModel` object. This model may then be evaluated using the `mxRun` function. The results of the optimization can be found in the 'output' slot of the resulting model, and may be obtained using the `mxEval` function.

### Value

Returns a new `MxExpectationStateSpace` object. `mxExpectationStateSpace` objects should be included with models with referenced `MxAlgebra`, `MxData` and `MxMatrix` objects.

### References

K.J. Åström and R.M. Murray (2010). *Feedback Systems: An Introduction for Scientists and Engineers*. Princeton University Press.

J. Durbin and S.J. Koopman. (2001). *Time Series Analysis by State Space Methods*. Oxford University Press.

R.E. Kalman (1960). A New Approach to Linear Filtering and Prediction Problems. *Basic Engineering*, 82, 35-45.

G. Petris (2010). An R Package for Dynamic Linear Models. *Journal of Statistical Software*, 36, 1-16.

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

### See Also

[mxExpectationStateSpaceContinuousTime](#)

### Examples

```
# Create and fit a model using mxMatrix, mxExpectationStateSpace, and mxFitFunctionML
require(OpenMx)
data(demoOneFactor)
nvar <- ncol(demoOneFactor)
varnames <- colnames(demoOneFactor)
ssModel <- mxModel(model="State Space Manual Example",
  mxMatrix("Full", 1, 1, TRUE, .3, name="A"),
```



```

    mxMatrix("Zero", 1, 1, name="B"),
    mxMatrix("Full", nvar, 1, TRUE, .6, name="C", dimnames=list(varnames, "F1")),
    mxMatrix("Zero", nvar, 1, name="D"),
    mxMatrix("Diag", 1, 1, FALSE, 1, name="Q"),
    mxMatrix("Diag", nvar, nvar, TRUE, .2, name="R"),
    mxMatrix("Zero", 1, 1, name="x0"),
    mxMatrix("Diag", 1, 1, FALSE, 1, name="P0"),
    mxMatrix("Zero", 1, 1, name="u"),
    mxData(observed=demoOneFactor[1:100,], type="raw"),#fewer rows = fast
    mxExpectationStateSpace("A", "B", "C", "D", "Q", "R", "x0", "P0", "u"),
    mxFitFunctionML()
)
ssRun <- mxRun(ssModel)
summary(ssRun)
# Note the freely estimated Autoregressive parameter (A matrix)
# is near zero as it should be for the independent rows of data
# from the factor model.

# Create and fit a model with INPUTS using mxMatrix, mxExpectationStateSpace, and mxFitFunctionML
require(OpenMx)
data(demoOneFactor)
nvar <- ncol(demoOneFactor)
varnames <- colnames(demoOneFactor)
#demoOneFactorInputs <- cbind(demoOneFactor, V1=rep(1, nrow(demoOneFactor)))
demoOneFactorInputs <- cbind(demoOneFactor, V1=rnorm(nrow(demoOneFactor)))
ssModel <- mxModel(model="State Space Inputs Manual Example",
  mxMatrix("Full", 1, 1, TRUE, .3, name="A"),
  mxMatrix("Full", 1, 1, TRUE, values=1, name="B"),
  mxMatrix("Full", nvar, 1, TRUE, .6, name="C", dimnames=list(varnames, "F1")),
  mxMatrix("Zero", nvar, 1, name="D"),
  mxMatrix("Diag", 1, 1, FALSE, 1, name="Q"),
  mxMatrix("Diag", nvar, nvar, TRUE, .2, name="R"),
  mxMatrix("Zero", 1, 1, name="x0"),
  mxMatrix("Diag", 1, 1, FALSE, 1, name="P0"),
  mxMatrix("Full", 1, 1, FALSE, labels="data.V1", name="u"),
  mxData(observed=demoOneFactorInputs[1:100,], type="raw"),#fewer rows = fast
  mxExpectationStateSpace("A", "B", "C", "D", "Q", "R", "x0", "P0", u="u"),
  mxFitFunctionML()
)
ssRun <- mxRun(ssModel)
summary(ssRun)
# Note the freely estimated Autoregressive parameter (A matrix)
# and the freely estimated Control-Input parameter (B matrix)
# are both near zero as they should be for the independent rows of data
# from the factor model that does not have inputs, covariates,
# or exogenous variables.

```

---

mxExpectationStateSpaceContinuousTime

*Create an MxExpectationStateSpace Object*

---

**Description**

This function creates a new `MxExpectationStateSpace` object.

**Usage**

```
mxExpectationStateSpaceContinuousTime(A, B, C, D, Q, R, x0, P0, u, t = NA,
                                       dimnames = NA, thresholds = NA, threshnames = dimnames,
                                       ..., scores=FALSE)
mxExpectationSSCT(A, B, C, D, Q, R, x0, P0, u, t = NA,
                  dimnames = NA, thresholds = NA, threshnames = dimnames,
                  ..., scores=FALSE)
```

**Arguments**

A	A character string indicating the name of the 'A' matrix.
B	A character string indicating the name of the 'B' matrix.
C	A character string indicating the name of the 'C' matrix.
D	A character string indicating the name of the 'D' matrix.
Q	A character string indicating the name of the 'Q' matrix.
R	A character string indicating the name of the 'R' matrix.
x0	A character string indicating the name of the 'x0' matrix.
P0	A character string indicating the name of the 'P0' matrix.
u	A character string indicating the name of the 'u' matrix.
t	A character string indicating the name of the 't' matrix.
dimnames	An optional character vector to be assigned to the row names of the 'C' matrix.
thresholds	Not Yet Implemented. An optional character string indicating the name of the thresholds matrix.
threshnames	Not Yet Implemented. An optional character vector to be assigned to the column names of the thresholds matrix.
...	Unused. Requires further arguments to be named.
scores	Not to be used

**Details**

The `mxExpectationStateSpaceContinuousTime` and `mxExpectationSSCT` functions are identical. The latter is simply an abbreviated name. When using the former, tab completion is strongly encouraged to save tedious typing. Both of these functions are wrappers for the [mxExpectationStateSpace](#) function, which could be used for both discrete and continuous time modeling. However, there is a strong possibility of misunderstanding the model parameters when switching between discrete time and continuous time. The expectation matrices have the same names, but mean importantly different things so caution is warranted. The best practice is to use `mxExpectationStateSpace` for discrete time models, and `mxExpectationStateSpaceContinuousTime` for continuous time models.

Expectation functions define the way that model expectations are calculated. That is to say, expectation functions define how a set of model matrices get turned into expectations for the data. When used in conjunction with the `mxFitFunctionML`, the `mxExpectationStateSpace` uses maximum likelihood prediction error decomposition (PED) to obtain estimates of free parameters in a model of the raw `MxData` object. Continuous time state space expectations treat the raw data as a multivariate time series of possibly unevenly spaced times with each row corresponding to a single occasion. Continuous time state space expectations implement a hybrid Kalman filter to produce expectations. The hybrid Kalman filter uses a Kalman-Bucy filter for the prediction step and the classical Kalman filter for the update step. It is a hybrid between the classical Kalman filter used for the discrete (but possibly unequally spaced) measurement occasions and the continuous time Kalman-Bucy filter for latent variable predictions.

Missing data handling is implemented in the same fashion as full information maximum likelihood for partially missing rows of data. Additionally, completely missing rows of data are handled by only using the prediction step from the Kalman-Bucy filter and omitting the update step.

This model uses notation for the model matrices commonly found in engineering and control theory. The 'A', 'B', 'C', 'D', 'Q', 'R', 'x0', and 'P0' arguments must be the names of `MxMatrix` or `MxAlgebra` objects with the associated properties of the A, B, C, D, Q, R, x0, and P0 matrices in the state space modeling approach. The 't' matrix must be a 1x1 matrix using definition variables that gives the times at which measurements occurred.

The state space expectation is defined by the following model equations.

$$\frac{d}{dt}x(t) = Ax(t) + Bu_t + q(t)$$

$$y_t = Cx_t + Du_t + r_t$$

with  $q(t)$  and  $r_t$  both independently and identically distributed random Gaussian (normal) variables with mean zero and covariance matrices  $Q$  and  $R$ , respectively. Subscripts or square brackets indicate discrete indices; parentheses indicate continuous indices. The derivative of  $x(t)$  with respect to  $t$  is  $\frac{d}{dt}x(t)$ .

The first equation is called the state equation. It describes how the latent states change over time with a first-order linear differential equation. Unlike some other programs, we do not require that the continuous time  $A$  matrix has an inverse. This allows zero dynamics (i.e. no growth models) and many other important kinds of processes.

The second equation is called the output equation. It describes how the latent states relate to the observed states at a single point in time. The output equation shows how the observed output is produced by the latent states. Also, the output equation in state space modeling is directly analogous to the measurement model in LISREL structural equation modeling.

Note that the covariates,  $u$ , have "instantaneous" effects on both the state and output equations. If lagged effects are desired, then the user must create a lagged covariate by shifting their observed variable to the desired lag.

The state and output equations, together with some minimal assumptions and the Kalman filter, imply a new expected covariance matrix and means vector for every row of data. The expected covariance matrix of row  $t$  is

$$S_t = C(AP_{t-1}A^T + Q)C^T + R$$

The expected means vector of row  $t$  is

$$\hat{y}_t = Cx_t + Du_t$$

The 'dimnames' argument takes an optional character vector.

The 'A' argument refers to the  $A$  matrix in the State Space approach. This matrix gives the dynamics. Entries in the diagonal give the strength of the influence of a variable's position on its slope. Entries in the off-diagonal give the coupling strength from one variable to another. The  $A$  matrix is sometimes called the state-transition model.

The 'B' argument refers to the  $B$  matrix in the State Space approach. This matrix consists of exogenous forces that influence the dynamics. Note that the covariate effect is contemporaneous: the covariate at time  $t$  has influence on the slope of the latent state also at time  $t$ . A lagged effect can be created by lagged the observed variable. The  $B$  matrix is sometimes called the control-input model.

The 'C' argument refers to the  $C$  matrix in the State Space approach. This matrix consists of contemporaneous regression coefficients from the latent variable in column  $j$  to the observed variable in row  $i$ . This matrix is directly analogous to the factor loadings matrix in LISREL and Mplus models. The  $C$  matrix is sometimes called the observation model.

The 'D' argument refers to the  $D$  matrix in the State Space approach. This matrix consists of contemporaneous regressive coefficients from the input (manifest covariate) variable  $j$  to the observed variable in row  $i$ . The  $D$  matrix is sometimes called the feedthrough or feedforward matrix.

The 'Q' argument refers to the  $Q$  matrix in the State Space approach. This matrix gives the covariance of the dynamic noise. The dynamic noise can be thought of as unmeasured covariate inputs active at all times. This matrix must be symmetric, diagonal, or zero. As a special case, it is often diagonal. The  $Q$  matrix is the covariance of the process noise. Just as in factor analysis and general structural equation modeling, the scale of the latent variables is usually set by fixing some factor loadings in the  $C$  matrix, or fixing some factor variances in the  $Q$  matrix.

The 'R' argument refers to the  $R$  matrix in the State Space approach. This matrix consists of residual covariances among the observed (manifest) variables. This matrix must be symmetric. As a special case, it is often diagonal. The  $R$  matrix is the covariance of the observation noise.

The 'x0' argument refers to the  $x_0$  matrix in the State Space approach. This matrix consists of the column vector of the initial values for the latent variables. The state space expectation uses the  $x_0$  matrix as the starting point to recursively estimate the latent variables' values at each time. These starting values can be difficult to pick, however, for sufficiently long time series they often do not greatly impact the estimation.

The 'P0' argument refers to the  $P_0$  matrix in the State Space approach. This matrix consists of the initial values of the covariances of the error in the initial latent variable estimates given in  $x_0$ . That is, the  $P_0$  matrix gives the covariance of  $x_0 - x_{true_0}$  where  $x_{true_0}$  is the vector of true initial values.  $P_0$  is a measure of the accuracy of the initial latent state estimates. The Kalman filter uses this initial covariance to recursively generate a new covariance for each time point based on the previous time point. The Kalman filter updates this covariance so that it is as small as possible (minimum trace). Similar to the  $x_0$  matrix, these starting values are often difficult to choose.

The 'u' argument refers to the  $u$  matrix in the State Space approach. This matrix consists of the inputs or manifest covariates of the state space expectation. The  $u$  matrix must be a column vector with the same number of rows as the  $B$  and  $D$  matrices have columns. If no inputs are desired,  $u$

can be a zero matrix. If time-varying inputs are desired, then they should be included as columns in the `MxData` object and referred to in the labels of the  $u$  matrix as definition variables. There is an example of this below.

The 't' argument refers to the  $t$  matrix in the State Space approach. This matrix should be 1x1 (1 row and 1 column) and not free. The label for the element of this matrix should be 'data.YourTimeVariable'. The 'data' part does not change, but 'YourTimeVariable' should be a name in your data set that gives the times at which measurement happened. The units of time are up to you. Your choice of time units will influence of the values of the parameters you estimate. Also, recall that the model is given  $x_0$  and  $P_0$ . These always happen at  $t = 0$ . So the first row of data happens some amount of time after zero.

The `MxMatrix` objects included as arguments may be of any type, but should have the properties described above. The `mxExpectationStateSpace` will not return an error for incorrect specification, but incorrect specification will likely lead to estimation problems or errors in the `mxRun` function.

`mxExpectationStateSpaceContinuousTime` evaluates with respect to an `MxData` object. The `MxData` object need not be referenced in the `mxExpectationStateSpace` function, but must be included in the `MxModel` object. `mxExpectationStateSpace` requires that the 'type' argument in the associated `MxData` object be equal to 'raw'. Neighboring rows of the `MxData` object are treated as adjacent, equidistant time points increasing from the first to the last row.

To evaluate, place an `mxExpectationStateSpaceContinuousTime` object, the `mxData` object for which the expected covariance approximates, referenced `MxAlgebra` and `MxMatrix` objects, and optional `MxBounds` and `MxConstraint` objects in an `MxModel` object. This model may then be evaluated using the `mxRun` function. The results of the optimization can be found in the 'output' slot of the resulting model, and may be obtained using the `mxEval` function.

## Value

Returns a new `MxExpectationStateSpace` object. `mxExpectationStateSpace` objects should be included with models with referenced `MxAlgebra`, `MxData` and `MxMatrix` objects.

## References

K.J. Åström and R.M. Murray (2010). *Feedback Systems: An Introduction for Scientists and Engineers*. Princeton University Press.

J. Durbin and S.J. Koopman. (2001). *Time Series Analysis by State Space Methods*. Oxford University Press.

R.E. Kalman (1960). A New Approach to Linear Filtering and Prediction Problems. *Basic Engineering*, 82, 35-45.

R.E. Kalman and R.S. Bucy (1961). New Results in Linear Filtering and Prediction Theory. *Transactions of the ASME, Series D, Journal of Basic Engineering*, 83, 95-108.

G. Petris (2010). An R Package for Dynamic Linear Models. *Journal of Statistical Software*, 36, 1-16.

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

[mxExpectationStateSpace](#)

**Examples**

```

#-----
# Example 1
# Undamped linear oscillator, i.e. a noisy sine wave.
# Measurement error, but no dynamic error, single indicator.
# This example works great.

#-----
# Data Generation

require(OpenMx)

set.seed(405)
tlen <- 200
t <- seq(1.2, 50, length.out=tlen)

freqParam <- .5
initialCond <- matrix(c(2.5, 0))
x <- initialCond[1,1]*cos(freqParam*t)
plot(t, x, type='l')

measVar <- 1.5
y <- cbind(obs=x+rnorm(tlen, sd=sqrt(measVar)), tim=t)

plot(t, y[,1], type='l')

#-----
# Model Specification

#Note: the bounds are here only to keep SLSQP from
# stepping too far off a cliff. With the bounds in
# place, SLSQP finds the right solution. Without
# the bounds, SLSQP goes crazy.

cdim <- list('obs', c('ksi', 'ksiDot'))

amat <- mxMatrix('Full', 2, 2, c(FALSE, TRUE, FALSE, TRUE), c(0, -.1, 1, -.2),
name='A', lbound=-10)
bmat <- mxMatrix('Zero', 2, 1, name='B')
cmat <- mxMatrix('Full', 1, 2, FALSE, c(1, 0), name='C', dimnames=cdim)
dmat <- mxMatrix('Zero', 1, 1, name='D')
qmat <- mxMatrix('Zero', 2, 2, name='Q')
rmat <- mxMatrix('Diag', 1, 1, TRUE, .4, name='R', lbound=1e-6)
xmat <- mxMatrix('Full', 2, 1, TRUE, c(0, 0), name='x0', lbound=-10, ubound=10)
pmat <- mxMatrix('Diag', 2, 2, FALSE, 1, name='P0')
umat <- mxMatrix('Zero', 1, 1, name='u')
tmat <- mxMatrix('Full', 1, 1, name='time', labels='data.tim')

osc <- mxModel("LinearOscillator",
amat, bmat, cmat, dmat, qmat, rmat, xmat, pmat, umat, tmat,
mxExpectationSSCT('A', 'B', 'C', 'D', 'Q', 'R', 'x0', 'P0', 'u', 'time'),

```

```

mxFitFunctionML(),
mxData(y, 'raw'))

oscr <- mxRun(osc)

#-----
# Results Examination

summary(oscr)

(ssFreqParam <- mxEval(sqrt(-A[2,1]), oscr))
freqParam

(ssMeasVar <- mxEval(R, oscr))
measVar

dampingParam <- 0
(ssDampingParam <- mxEval(-A[2,2], oscr))
dampingParam

```

---

mxFactor

*Fail-safe Factors*


---

## Description

This is a wrapper for the R function [factor](#).

OpenMx requires ordinal data to be ordered. R's `factor` function doesn't enforce this, hence this wrapper exists to throw an error should you accidentally try and run with `ordered = FALSE`.

Also, the 'levels' parameter is optional in R's `factor` function. However, relying on the data to specify the data is foolhardy for the following reasons: The `factor` function will skip levels missing from the data: Specifying these in levels leaves the list of levels complete. Data will often not explore the min and max level that the user knows are possible. For these reasons this function forces you to write out all possible levels explicitly.

## Usage

```

mxFactor(x = character(), levels, labels = levels,
         exclude = NA, ordered = TRUE, collapse = FALSE)

```

**Arguments**

x	either a vector of data or a data.frame object.
levels	a mandatory vector of the values that 'x' might have taken.
labels	<code>_either_</code> an optional vector of labels for the levels, <code>_or_</code> a character string of length 1.
exclude	a vector of values to be excluded from the set of levels.
ordered	logical flag to determine if the levels should be regarded as ordered (in the order given). Required to be TRUE.
collapse	logical flag to determine if duplicate labels should collapsed into a single level

**Details**

If 'x' is a data.frame, then all of the columns of 'x' are converted into ordered factors. If 'x' is a data.frame, then 'levels' and 'labels' may be either a list or a vector. When 'levels' is a list, then different levels are assigned to different columns of the constructed data.frame object. When 'levels' is a vector, then the same levels are assigned to all the columns of the data.frame object. The function will throw an error if 'ordered' is not TRUE or if 'levels' is missing. See [factor](#) for more information on creating ordered factors.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
myVar <- c("s", "t", "a", "t", "i", "s", "t", "i", "c", "s")
ff <- mxFactor(myVar, levels=letters)
# Note: letters is a built in list of all lowercase letters of the alphabet
ff
# [1] s t a t i s t i c s
# Levels: a < b < c < d < e < f < g < h < i < j < k < l < m < n < o < p < q <
# r < s < t < u < v < w < x < y < z

as.integer(ff) # the internal codes

factor(ff) # NOTE: drops the levels that do not occur.
# mxFactor prevents you doing this unintentionally.

# This example works on a dataframe
foo <- data.frame(x=c(1:3),y=c(4:6),z=c(7:9))

# Applies one set of levels to all three columns
mxFactor(foo, c(1:9))

# Apply unique sets of levels to each variable
mxFactor(foo, list(c(1:3), c(4:6), c(7:9)))

mxFactor(foo, c(1:9), labels=c(1,1,1,2,2,2,3,3,3), collapse=TRUE)
```



---

mxFactorScores	<i>Estimate factor scores and standard errors</i>
----------------	---

---

### Description

This function creates the factor scores and their standard errors under different methods for an MxModel object that has either a RAM or LISREL expectation.

### Usage

```
mxFactorScores(model, type=c('ML', 'WeightedML', 'Regression'),
  minManifests=as.integer(NA))
```

### Arguments

model	An MxModel object with either an MxExpectationLISREL or MxExpectationRAM
type	The type of factor scores to compute
minManifests	Set scores to NA when there are less than minManifests non-NA manifest variables

### Details

This is a helper function to compute or estimate factor scores along with their standard errors. The two maximum likelihood methods create a new model for each data row. They then estimate the factor scores as free parameters in a model with a single data row. For 'ML', the conditional likelihood of the data given the factor scores is optimized:

$$L(D|F)$$

. For 'WeightedML', the joint likelihood of the data and the factor scores is optimized:

$$L(D, F) = L(D|F)L(F)$$

. The WeightedML scores are akin to the empirical Bayes random effects estimates from mixed effects modeling. They display the same kind of shrinkage as random effects estimates, and for the same reason: they account for the latent variable distribution in their estimation.

In many cases, especially for ordinal data or missing data, the weighted ML scores are to be preferred over alternatives (Estabrook & Neale, 2013). For example, when using ordinal data, a person whose observations are all in the highest ordinal category theoretically has an 'ML' factor score of positive infinity. A similar situation arises for a person whose observations are all in the lowest ordinal category: their 'ML' factor score is theoretically negative infinity. Weighted ML factor scores in these cases remain reasonable.

For type='Regression', with LISREL expectation, factor scores are computed based on a simple formula. This formula is equivalent to the formula for the Kalman updated scores in a state space model with zero dynamics (Priestly & Subba Rao, 1975). Thus, to compute the regression factor



```

      mxPath(from=manifests, arrows=2),
      mxPath(from=latents, arrows=2, free=FALSE, values=1.0),
      mxPath(from='one', to=manifests),
      mxData(observed=cov(demoOneFactor), type="cov", numObs=500,
              means = colMeans(demoOneFactor)))
summary(factorRun <- mxRun(factorModel))

# Swap in raw data in place of summary data
factorRun <- mxModel(factorRun, mxData(observed=demoOneFactor[1:50,], type="raw"))

# Estimate factor scores for the model
r1 <- mxFactorScores(factorRun, 'Regression')

```

---

mxFIMLObjective

*DEPRECATED: Create MxFIMLObjective Object*


---

## Description

WARNING: Objective functions have been deprecated as of OpenMx 2.0.

Please use `mxExpectationNormal()` and `mxFitFunctionML()` instead. As a temporary workaround, `mxFIMLObjective` returns a list containing an `MxExpectationNormal` object and an `MxFitFunctionML` object.

All occurrences of

`mxFIMLObjective(covariance, means, dimnames = NA, thresholds = NA, vector = FALSE, threshnames = dimnames)`

Should be changed to

`mxExpectationNormal(covariance, means, dimnames = NA, thresholds = NA, threshnames = dimnames) mxFitFunctionML(vector = FALSE)`

## Arguments

<code>covariance</code>	A character string indicating the name of the expected covariance algebra.
<code>means</code>	A character string indicating the name of the expected means algebra.
<code>dimnames</code>	An optional character vector to be assigned to the <code>dimnames</code> of the covariance and means algebras.
<code>thresholds</code>	An optional character string indicating the name of the thresholds matrix.
<code>vector</code>	A logical value indicating whether the objective function result is the likelihood vector.
<code>threshnames</code>	An optional character vector to be assigned to the column names of the thresholds matrix.

## Details

NOTE: THIS DESCRIPTION IS DEPRECATED. Please change to using [mxExpectationNormal](#) and [mxFitFunctionML](#) as shown in the example below.

Objective functions were functions for which free parameter values are chosen such that the value of the objective function is minimized. The `mxFIMLObjective` function used full-information maximum likelihood to provide maximum likelihood estimates of free parameters in the algebra defined by the 'covariance' and 'means' arguments. The 'covariance' argument takes an [MxAlgebra](#) object, which defines the expected covariance of an associated [MxData](#) object. The 'means' argument takes an [MxAlgebra](#) object, which defines the expected means of an associated [MxData](#) object. The 'dimnames' arguments takes an optional character vector. If this argument is not a single NA, then this vector is used to assign the dimnames of the means vector as well as the row and columns dimnames of the covariance matrix.

The 'vector' argument is either TRUE or FALSE, and determines whether the objective function returns a column vector of the likelihoods, or a single  $-2 * (\log \text{likelihood})$  value.

`thresholds`: The name of the thresholds matrix. When needed (for modelling ordinal data), this matrix should be created using [mxMatrix\(\)](#). The thresholds matrix must have as many columns as there are ordinal variables in the model, and number of rows equal to one fewer than the maximum number of levels found in the ordinal variables. The starting values of this matrix must also be set to reasonable values. Fill each column with a set of ordered start thresholds, one for each level of this column's factor levels minus 1. These thresholds may be free if you wish them to be estimated, or fixed. The unused rows in each column, if any, can be set to any value including NA.

`threshnames`: A character vector consisting of the variables in the thresholds matrix, i.e., the names of ordinal variables in a model. This is necessary for OpenMx to map the thresholds matrix columns onto the variables in your data. If you set the `dimnames` of the columns in the thresholds matrix then `threshnames` is not needed.

Usage Notes: `dimnames` must be supplied where the matrices referenced by the covariance and means algebras are not themselves labeled. Failure to do so leads to an error noting that the covariance or means matrix associated with the FIML objective does not contain dimnames.

`mxFIMLObjective` evaluates with respect to an [MxData](#) object. The [MxData](#) object need not be referenced in the `mxFIMLObjective` function, but must be included in the [MxModel](#) object. `mx-FIMLObjective` requires that the 'type' argument in the associated [MxData](#) object be equal to 'raw'. Missing values are permitted in the associated [MxData](#) object.

To evaluate, place `mxFIMLObjective` objects, the [mxData](#) object for which the expected covariance approximates, referenced [MxAlgebra](#) and [MxMatrix](#) objects, and optional [MxBounds](#) and [MxConstraint](#) objects in an [MxModel](#) object. This model may then be evaluated using the [mxRun](#) function.

The results of the optimization can be reported using the [summary](#) function, or accessed directly in the 'output' slot of the resulting model (i.e., `modelName$output`). Components of the output may be referenced using the [Extract](#) functionality.

## Value

Returns a list containing an [MxExpectationNormal](#) object and an [MxFitFunctionML](#) object.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```

# Create and fit a model using mxMatrix, mxAlgebra, mxExpectationNormal, and mxFitFunctionML

library(OpenMx)

# Simulate some data

x=rnorm(1000, mean=0, sd=1)
y= 0.5*x + rnorm(1000, mean=0, sd=1)
tmpFrame <- data.frame(x, y)
tmpNames <- names(tmpFrame)

# Define the matrices

M <- mxMatrix(type = "Full", nrow = 1, ncol = 2, values=c(0,0),
              free=c(TRUE,TRUE), labels=c("Mx", "My"), name = "M")
S <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(1,0,0,1),
              free=c(TRUE,FALSE,FALSE,TRUE), labels=c("Vx", NA, NA, "Vy"), name = "S")
A <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(0,1,0,0),
              free=c(FALSE,TRUE,FALSE,FALSE), labels=c(NA, "b", NA, NA), name = "A")
I <- mxMatrix(type="Iden", nrow=2, ncol=2, name="I")

# Define the expectation

expCov <- mxAlgebra(solve(I-A) %*% S %*% t(solve(I-A)), name="expCov")
expFunction <- mxExpectationNormal(covariance="expCov", means="M", dimnames=tmpNames)

# Choose a fit function

fitFunction <- mxFitFunctionML()

# Define the model

tmpModel <- mxModel(model="exampleModel", M, S, A, I, expCov, expFunction, fitFunction,
                    mxData(observed=tmpFrame, type="raw"))

# Fit the model and print a summary

tmpModelOut <- mxRun(tmpModel)
summary(tmpModelOut)

```

---

MxFitFunction-class    *MxFitFunction*

---

**Description**

This is an internal class and should not be used directly.

---

 mxFitFunctionAlgebra *Create MxFitFunctionAlgebra Object*


---

### Description

mxFitFunctionAlgebra returns an MxFitFunctionAlgebra object.

### Usage

```
mxFitFunctionAlgebra(algebra, numObs = NA, numStats = NA, ..., gradient =
  NA_character_, hessian = NA_character_, verbose = 0L, units="-2lnL")
```

### Arguments

algebra	A character string indicating the name of an <a href="#">MxAlgebra</a> or <a href="#">MxMatrix</a> object to use for optimization.
numObs	(optional) An adjustment to the total number of observations in the model.
numStats	(optional) An adjustment to the total number of observed statistics in the model.
...	Not used. Forces remaining arguments to be specified by name.
gradient	(optional) A character string indicating the name of an <a href="#">MxAlgebra</a> object.
hessian	(optional) A character string indicating the name of an <a href="#">MxAlgebra</a> object.
verbose	(optional) An integer to increase the level of runtime log output.
units	(optional) The units of the fit statistic.

### Details

If you want to fit a multigroup model, the preferred way is to use [mxFitFunctionMultigroup](#).

Fit functions are functions for which free parameter values are chosen such that the value of the objective function is minimized. While the other fit functions in OpenMx require an expectation function for the model, the `mxAlgebraObjective` function uses the referenced [MxAlgebra](#) or [MxMatrix](#) object as the function to be minimized.

If a model's fit function is an `mxFitFunctionAlgebra` objective function, then the referenced algebra in the objective function must return a 1 x 1 matrix (when using OpenMx's default optimizer). There is no restriction on the dimensions of an fit function that is not the primary, or 'topmost', objective function.

To evaluate an algebra fit function, place the following objects in a [MxModel](#) object: a `mxFitFunctionAlgebra`, [MxAlgebra](#) and [MxMatrix](#) entities referenced by the `mxAlgebraObjective`, and optional [MxBounds](#) and [MxConstraint](#) objects. This model may then be evaluated using the [mxRun](#) function. The results of the optimization may be obtained using the [mxEval](#) function on the name of the [MxAlgebra](#), after the model has been run.

First and second derivatives can be provided with the algebra fit function. The dimnames on the gradient and hessian [MxAlgebras](#) are matched against names of free variables. Names that do not match are ignored. The fit is assumed to be in deviance units (-2 log likelihood units). If you are working in log likelihood units, the -2 scaling factor is not applied automatically. You have to multiply by -2 yourself.

**Value**

Returns an MxFitFunctionAlgebra object. MxFitFunctionAlgebra objects should be included with models with referenced [MxAlgebra](#) and [MxMatrix](#) objects.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

Other fit functions: [mxFitFunctionMultigroup](#), [mxFitFunctionML](#), [mxFitFunctionWLS](#), [mxFitFunctionGREML](#), [mxFitFunctionR](#), [mxFitFunctionRow](#)

To create an algebra suitable as a reference function to be minimized see: [mxAlgebra](#)

More information about the OpenMx package may be found [here](#).

**Examples**

```
# Create and fit a very simple model that adds two numbers using mxFitFunctionAlgebra

library(OpenMx)

# Create a matrix 'A' with no free parameters
A <- mxMatrix('Full', nrow = 1, ncol = 1, values = 1, name = 'A')

# Create an algebra 'B', which defines the expression A + A
B <- mxAlgebra(A + A, name = 'B')

# Define the objective function for algebra 'B'
objective <- mxFitFunctionAlgebra('B')

# Place the algebra, its associated matrix and
# its objective function in a model
tmpModel <- mxModel(model="Addition", A, B, objective)

# Evaluate the algebra
tmpModelOut <- mxRun(tmpModel)

# View the results
tmpModelOut$output$minimum
```

---

`mxFitFunctionGREML`*Create MxFitFunctionGREML Object*

---

**Description**

This function creates a new [MxFitFunctionGREML](#) object.

**Usage**

```
mxFitFunctionGREML(dV=character(0), aug=character(0),
  augGrad=character(0), augHess=character(0))
```

**Arguments**

dV	Vector of character strings; defaults to a character vector of length zero. If a value of non-zero length is provided, it must be a <i>named</i> character vector. This vector's names must be the labels of each free parameter in the model. The vector's elements (i.e., the character strings themselves) must be the names of <a href="#">MxAlgebra</a> or <a href="#">MxMatrix</a> object(s), each of which equals the first partial derivative of the 'V' matrix with respect to the corresponding free parameter.
aug	Character string; defaults to a character vector of length zero. Any elements after the first are ignored. The string should name a 1x1 <a href="#">MxMatrix</a> or an <a href="#">MxAlgebra</a> that evaluates to a 1x1 matrix. The named object will be used as an "augmentation" to the GREML fitfunction—specifically, the [1,1] value of the object named by aug will be added to the GREML fitfunction value at each function evaluation during optimization. The augmentation can be used to regularize estimation with a prior likelihood, or to use penalty functions to approximate constraints.
augGrad	Character string; defaults to a character vector of length zero. Any elements after the first are ignored. The string should name a <a href="#">MxMatrix</a> or an <a href="#">MxAlgebra</a> that evaluates to the gradient of aug with respect to free parameters. The gradient can be either a column or row vector. The free parameters corresponding to the elements of the gradient vector are taken from the names of argument dV, e.g. if the third name of dV is 'va', then the third element of the gradient vector should be the first partial derivative of the augmentation function with respect to 'va'. Ignored unless both dV and aug have nonzero length.
augHess	Character string; defaults to a character vector of length zero. Any elements after the first are ignored. The string should name a <a href="#">MxMatrix</a> or an <a href="#">MxAlgebra</a> that evaluates to the Hessian of aug with respect to free parameters. The free parameters corresponding to each row and column of this matrix are dictated by the names of argument dV, in the same manner as for the elements of augGrad. Ignored unless both dV and aug have nonzero length. Providing a nonzero-length value for augHess but not augGrad will result in an error at runtime.

**Details**

Making effective use of arguments dV, augGrad, and augHess will usually require a custom [mxComputeSequence\(\)](#).

The derivatives of the REML loglikelihood function with respect to parameters can be internally computed from the derivatives of the 'V' matrix supplied via dV. These loglikelihood derivatives will be valid as long as (1) the derivatives of 'V' evaluate to symmetric matrices the same size as 'V,' and (2) the model contains no [MxConstraints](#). Internally, the derivatives of the 'V' matrix are assumed to be symmetric, and the elements above their main diagonals are ignored.

Currently, if any derivatives are provided via dV, then derivatives must be provided for *every* free parameter in the MxModel.

Argument aug is intended to allow users to provide penalty functions or prior likelihoods in order to approximate constraints or to regularize optimization. The user is warned that careless use of this



augmentation feature may undermine the validity of his/her statistical inferences.

### Value

Returns a new object of class `MxFitFunctionGREML`.

### References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

### See Also

See `MxFitFunctionGREML` for the S4 class created by `mxFitFunctionGREML()`. For more information generally concerning GREML analyses, including a complete example, see `mxEExpectationGREML()`.

Other fit functions: `mxFitFunctionMultigroup`, `mxFitFunctionML`, `mxFitFunctionWLS`, `mxFitFunctionAlgebra`, `mxFitFunctionR`, `mxFitFunctionRow`

More information about the OpenMx package may be found [here](#).

### Examples

```
gff <- mxFitFunctionGREML()
str(gff)
```

---

`MxFitFunctionGREML`-class

*Class "MxFitFunctionGREML"*

---

### Description

`MxFitFunctionGREML` is the fitfunction class for GREML analyses.

### Objects from the Class

Objects can be created by calls of the form `mxFitFunctionGREML(dV)`.

### Slots

**dV:** Object of class "MxCharOrNumber". Identifies the `MxAlgebra` or `MxMatrix` object(s) to serve as the derivatives of 'V' with respect to free parameters.

**dVnames:** Vector of character strings; names of the free parameters corresponding to slot dV.

**MLfit:** Object of class "numeric", equal to the maximum-likelihood fitfunction value (as opposed to the restricted maximum-likelihood value).

**numObs:** Object of class "integer". Number of observations.

**aug:** Object of class "MxCharOrNumber". Identifies the `MxAlgebra` or `MxMatrix` object used to "augment" the fitfunction value at each function evaluation during optimization.

augGrad: Object of class "MxCharOrNumber". Identifies the `MxAlgebra` or `MxMatrix` object(s) to serve as the first derivatives of aug with respect to free parameters.

augHess: Object of class "MxCharOrNumber". Identifies the `MxAlgebra` or `MxMatrix` object(s) to serve as the second derivatives of aug with respect to free parameters.

info: Object of class "list".

dependencies: Object of class "integer".

expectation: Object of class "integer".

vector: Object of class "logical".

rowDiagnostics: Object of class "logical".

result: Object of class "matrix".

name: Object of class "character".

### Extends

Class "MxBaseFitFunction", directly. Class "MxBaseNamed", by class "MxBaseFitFunction", distance 2. Class "MxFitFunction", by class "MxBaseFitFunction", distance 2.

### Methods

No methods defined with class "MxFitFunctionGREML" in the signature.

### References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

### See Also

See `mxFitFunctionGREML()` for creating `MxFitFunctionGREML` objects. See `mxExpectationGREML()` for creating `MxExpectationGREML` objects, and for more information generally concerning GREML analyses, including a complete example. More information about the OpenMx package may be found [here](#).

### Examples

```
showClass("MxFitFunctionGREML")
```

---

mxFitFunctionML

*Create MxFitFunctionML Object*

---

### Description

This function creates a new `MxFitFunctionML` object.

**Usage**

```
mxFitFunctionML(vector = FALSE, rowDiagnostics = FALSE, ..., fellner =
  as.logical(NA), verbose=0L, profileOut=c(),
  rowwiseParallel=as.logical(NA), jointConditionOn = c("auto", "ordinal", "continuous"))
```

**Arguments**

vector	A logical value indicating whether the objective function result is the likelihood vector.
rowDiagnostics	A logical value indicating whether the row-wise results of the objective function should be returned as an attribute of the fit function.
...	Not used. Forces remaining arguments to be specified by name.
fellner	Whether to fully expand the covariance matrix for maximum flexibility.
verbose	Level of diagnostic output
profileOut	Character vector naming constant coefficients to profile out of the likelihood (sometimes known as REML)
rowwiseParallel	For raw data only, whether to use OpenMP to parallelize the evaluation of rows
jointConditionOn	The evaluation strategy when both continuous and ordinal data are present.

**Details**

Fit functions are functions for which free parameter values are optimized such that the value of a cost function is minimized. The `mxFitFunctionML` function computes  $-2 \times (\log \text{likelihood})$  of the data given the current values of the free parameters and the expectation function (e.g., [mxExpectationNormal](#) or [mxExpectationRAM](#)) selected for the model.

The 'vector' argument is either TRUE or FALSE, and determines whether the objective function returns a column vector of the likelihoods, or a single  $-2 \times (\log \text{likelihood})$  value.

The 'rowDiagnostics' argument is either TRUE or FALSE, and determines whether the row likelihoods are returned as an attribute of the fit function. It is sometimes useful to inspect the likelihoods for outliers, diagnostics, or other anomalies.

When `vector=FALSE` and `rowDiagnostics=TRUE`, `fitfunction` can be referenced in the model and included in algebras as a scalar. The row likelihoods are an attribute of the fit function but are not accessible in the model during optimization. The row likelihoods are accessible to the user after the model has been run.

By default, `jointConditionOn='auto'` and a heuristic will be used to select the fastest algorithm. Conditioning the continuous data on ordinal will be superior when there are relatively few unique ordinal patterns. Otherwise, conditioning the ordinal data on continuous will perform better when there are relatively many ordinal patterns.

Usage Notes:

The results of the optimization can be reported using the [summary](#) function, or accessed directly in the 'output' slot of the resulting model (i.e., `modelName$output`). Components of the output may be referenced using the [Extract](#) functionality.

**Value**

Returns a new MxFitFunctionML object. One and only one MxFitFunctionML object should be included in each model along with an associated [mxExpectationNormal](#) or [mxExpectationRAM](#) object.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

Other fit functions: [mxFitFunctionMultigroup](#), [mxFitFunctionWLS](#), [mxFitFunctionAlgebra](#), [mxFitFunctionGREML](#), [mxFitFunctionR](#), [mxFitFunctionRow](#)

More information about the OpenMx package may be found [here](#).

**Examples**

```
# Create and fit a model using mxMatrix, mxAlgebra, mxExpectationNormal, and mxFitFunctionML

library(OpenMx)

# Simulate some data

x=rnorm(1000, mean=0, sd=1)
y= 0.5*x + rnorm(1000, mean=0, sd=1)
tmpFrame <- data.frame(x, y)
tmpNames <- names(tmpFrame)

# Define the matrices

M <- mxMatrix(type = "Full", nrow = 1, ncol = 2, values=c(0,0),
              free=c(TRUE,TRUE), labels=c("Mx", "My"), name = "M")
S <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(1,0,0,1),
              free=c(TRUE,FALSE,FALSE,TRUE), labels=c("Vx", NA, NA, "Vy"), name = "S")
A <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(0,1,0,0),
              free=c(FALSE,TRUE,FALSE,FALSE), labels=c(NA, "b", NA, NA), name = "A")
I <- mxMatrix(type="Iden", nrow=2, ncol=2, name="I")

# Define the expectation

expCov <- mxAlgebra(solve(I-A) %*% S %*% t(solve(I-A)), name="expCov")
expFunction <- mxExpectationNormal(covariance="expCov", means="M", dimnames=tmpNames)

# Choose a fit function

fitFunction <- mxFitFunctionML(rowDiagnostics=TRUE)
# also return row likelihoods, even though the fit function
# value is still 1x1

# Define the model
```

```

tmpModel <- mxModel(model="exampleModel", M, S, A, I, expCov, expFunction, fitFunction,
                    mxData(observed=tmpFrame, type="raw"))

# Fit the model and print a summary

tmpModelOut <- mxRun(tmpModel)
summary(tmpModelOut)

fitResOnly <- mxEval(fitfunction, tmpModelOut)
attributes(fitResOnly) <- NULL
fitResOnly

# Look at the row likelihoods alone
fitLikeOnly <- attr(mxEval(fitfunction, tmpModelOut), 'likelihoods')
head(fitLikeOnly)

```

---

```
mxFitFunctionMultigroup
```

*Create MxFitFunctionMultigroup object*

---

## Description

The fit function used to fit a multiple group model

## Usage

```
mxFitFunctionMultigroup(groups, ..., verbose = 0L)
```

## Arguments

groups	vector of fit function names (strings)
...	Not used. Forces subsequent arguments to be specified by name.
verbose	the level of debugging output

## Details

The `mxFitFunctionMultigroup` creates a fit function consisting of the sum of the fit statistics from a list of submodels provided. Thus, it aggregates fit statistics from multiple submodels.

This is conceptually similar to creating an [mxAlgebra](#) consisting of the sum of the subModel objectives and also creating an [mxFitFunctionAlgebra](#) to optimize the model based on this aggregate value.

This call to `mxFitFunctionMultigroup`:

```
mxFitFunctionMultigroup(c("model1", "model2"))
```

then, is almost equivalent to the following pair of statements:

```
mxAlgebra(model1.objective + model2.objective, name="myAlgebra")
mxFitFunctionAlgebra("myAlgebra")
```

The preferred method of specifying such a fit function is with this multigroup fit function, not the algebra fit function.

In addition to being more compact and readable, using `mxFitFunctionMultigroup` has additional side effects which are valuable for multi-group modeling.

Firstly, it aggregates analytic derivative calculations. Secondly, it allows `mxRefModels` to compute saturated models for raw data, as this function can learn which are the constituent submodels. Thirdly, it allows `mxCheckIdentification` to evaluate the local identification of the multigroup model.

Note: You can refer to the algebra generated by `mxFitFunctionMultigroup` when used in a group "modelName" as:

```
modelName.fitfunction
```

### See Also

Other fit functions: `mxFitFunctionML`, `mxFitFunctionWLS`, `mxFitFunctionAlgebra`, `mxFitFunctionGREML`, `mxFitFunctionR`, `mxFitFunctionRow`

More information about the OpenMx package may be found [here](#).

### Examples

```
#-----
# Brief non-running example
require("OpenMx")
mxFitFunctionMultigroup(c("model1", "model2")) # names of sub-models to be jointly optimised

#-----
# Longer, fully featured, running example
#
#
# Create and fit a model using mxMatrix, mxExpectationRAM, mxFitFunctionML,
# and mxFitFunctionMultigroup.
# The model is multiple group regression.
# Only the residual variances are allowed to differ across groups.

library(OpenMx)

# Simulate some data

# Group 1
N1=100
x=rnorm(N1, mean=0, sd=1)
y= 0.5*x + rnorm(N1, mean=0, sd=1)
ds1 <- data.frame(x, y)
dsNames <- names(ds1)
```

```

# Group 2
N2=150
x=rnorm(N2, mean=0, sd=1)
y= 0.5*x + rnorm(N2, mean=0, sd=sqrt(1.5))
ds2 <- data.frame(x, y)

# Define the matrices
M <- mxMatrix(type = "Full", nrow = 1, ncol = 2, values=0,
              free=TRUE, labels=c("Mx", "My"), name = "M")
S1 <- mxMatrix(type = "Diag", nrow = 2, ncol = 2, values=1,
              free=TRUE, labels=c("Vx", "ResidVy1"), name = "S")
S2 <- mxMatrix(type = "Diag", nrow = 2, ncol = 2, values=1,
              free=TRUE, labels=c("Vx", "ResidVy2"), name = "S")
A <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(0,1,0,0),
              free=c(FALSE,TRUE,FALSE,FALSE), labels=c(NA, "b", NA, NA),
              name = "A")
I <- mxMatrix(type="Iden", nrow=2, ncol=2, name="I")

# Define the expectation
expect <- mxExpectationRAM('A', 'S', 'I', 'M', dimnames=dsNames)

# Choose a fit function
fitFunction <- mxFitFunctionML(rowDiagnostics=TRUE)
# also return row likelihoods, even though the fit function
# value is still 1x1

# Multiple groupd fit function sums the model likelihoods
# from its component models
mgFitFun <- mxFitFunctionMultigroup(c('g1model', 'g2model'))

# Define the models
m1 <- mxModel(model="g1model", M, S1, A, I, expect, fitFunction,
              mxData(observed=cov(ds1), type="cov", numObs=nrow(ds1),
                    means=colMeans(ds1)))
m2 <- mxModel(model="g2model", M, S2, A, I, expect, fitFunction,
              mxData(observed=cov(ds2), type="cov", numObs=nrow(ds2),
                    means=colMeans(ds2)))
mg <- mxModel(model='multipleGroup', m1, m2, mgFitFun)

# Fit the model and print a summary

mgOut <- mxRun(mg)

# Look at summary of model
summary(mgOut)

# Examine fit function results
fitResOnly <- mxEval(fitfunction, mgOut)
( g1Fit <- mxEval(g1model.fitfunction, mgOut) )

```

```
( g2Fit <- mxEval(g2model.fitfunction, mgOut) )
```

---

mxFitFunctionR      *Create MxFitFunctionR Object*

---

### Description

mxFitFunctionR returns an MxFitFunctionR object.

### Usage

```
mxFitFunctionR(fitfun, ..., units="-2lnL")
```

### Arguments

fitfun	A function that accepts two arguments.
...	The initial state information to the objective function.
units	(optional) The units of the fit statistic.

### Details

The mxFitFunctionR function evaluates a user-defined R function called the 'fitfun'. mxFitFunctionR is useful in defining new mxFitFunctions, since any calculation that can be performed in R can be treated as an mxFitFunction.

The 'fitfun' argument must be a function that accepts two arguments. The first argument is the mxModel that should be evaluated, and the second argument is some persistent state information that can be stored between one iteration of optimization to the next iteration. It is valid for the function to simply ignore the second argument.

The function must return either a single numeric value, or a list of exactly two elements. If the function returns a list, the first argument must be a single numeric value and the second element will be the new persistent state information to be passed into this function at the next iteration. The single numeric value will be used by the optimizer to perform optimization.

The initial default value for the persistent state information is NA.

Throwing an exception (via stop) from inside fitfun may result in unpredictable behavior. You may want to wrap your code in tryCatch while experimenting.

fitfun should not call R functions that use OpenMx's compiled backend, including (but not limited to) `omxMnor()`, because doing so can crash R.

### Value

Returns an MxFitFunctionR object.



## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

Other fit functions: [mxFitFunctionMultigroup](#), [mxFitFunctionML](#), [mxFitFunctionWLS](#), [mxFitFunctionAlgebra](#), [mxFitFunctionGREML](#), [mxFitFunctionRow](#)

More information about the OpenMx package may be found [here](#).

## Examples

```
# Create and fit a model using mxFitFunctionR

library(OpenMx)

A <- mxMatrix(nrow = 2, ncol = 2, values = c(1:4), free = TRUE, name = 'A')
squared <- function(x) { x ^ 2 }

# Define the objective function in R

objFunction <- function(model, state) {
  values <- model$A$values
  return(squared(values[1,1] - 4) + squared(values[1,2] - 3) +
    squared(values[2,1] - 2) + squared(values[2,2] - 1))
}

# Define the expectation function

fitFunction <- mxFitFunctionR(objFunction)

# Define the model

tmpModel <- mxModel(model="exampleModel", A, fitFunction)

# Fit the model and print a summary

tmpModelOut <- mxRun(tmpModel)
summary(tmpModelOut)
```

---

mxFitFunctionRow

*Create an MxFitFunctionRow Object*

---

## Description

mxFitFunctionRow returns an MxFitFunctionRow object.

**Usage**

```
mxFitFunctionRow(rowAlgebra, reduceAlgebra, dimnames,
  rowResults = "rowResults", filteredDataRow = "filteredDataRow",
  existenceVector = "existenceVector", units="-2lnL")
```

**Arguments**

rowAlgebra	A character string indicating the name of the algebra to be evaluated row-wise.
reduceAlgebra	A character string indicating the name of the algebra that collapses the row results into a single number which is then optimized.
dimnames	A character vector of names corresponding to columns be extracted from the data set.
rowResults	The name of the auto-generated "rowResults" matrix. See details.
filteredDataRow	The name of the auto-generated "filteredDataRow" matrix. See details.
existenceVector	The name of the auto-generated "existenceVector" matrix. See details.
units	(optional) The units of the fit statistic.

**Details**

Fit functions are functions for which free parameter values are optimized such that the value of a cost function is minimized. The `mxFitFunctionRow` function evaluates a user-defined `MxAlgebra` object called the 'rowAlgebra' in a row-wise fashion. It then stores results of the row-wise evaluation in another `MxAlgebra` object called the 'rowResults'. Finally, the `mxFitFunctionRow` function collapses the row results into a single number which is then used for optimization. The `MxAlgebra` object named by the 'reduceAlgebra' collapses the row results into a single number.

The 'filteredDataRow' is populated in a row-by-row fashion with all the non-missing data from the current row. You cannot assume that the length of the filteredDataRow matrix remains constant (unless you have no missing data). The 'existenceVector' is populated in a row-by-row fashion with a value of 1.0 in column j if a non-missing value is present in the data set in column j, and a value of 0.0 otherwise. Use the functions `omxSelectRows`, `omxSelectCols`, and `omxSelectRowsAndCols` to shrink other matrices so that their dimensions will be conformable to the size of 'filteredDataRow'.

**Value**

Returns a new `MxFitFunctionRow` object. Only one `MxFitFunction` object should be included in each model. There is no need for an `MxExpectation` object when using `mxFitFunctionRow`.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

Other fit functions: `mxFitFunctionMultigroup`, `mxFitFunctionML`, `mxFitFunctionWLS`, `mxFitFunctionAlgebra`, `mxFitFunctionGREML`, `mxFitFunctionR`

More information about the OpenMx package may be found [here](#).

## Examples

```

# Model that adds two data columns row-wise, then sums that column
# Notice no optimization is performed here.

library(OpenMx)

xdat <- data.frame(a=rnorm(10), b=1:10) # Make data set
amod <- mxModel(model="example1",
  mxData(observed=xdat, type='raw'),
  mxAlgebra(sum(filteredDataRow), name = 'rowAlgebra'),
  mxAlgebra(sum(rowResults), name = 'reduceAlgebra'),
  mxFitFunctionRow(
    rowAlgebra='rowAlgebra',
    reduceAlgebra='reduceAlgebra',
    dimnames=c('a','b'))
)
amodOut <- mxRun(amod)
mxEval(rowResults, model=amodOut)
mxEval(reduceAlgebra, model=amodOut)

# Model that find the parameter that minimizes the sum of the
# squared difference between the parameter and a data row.

bmod <- mxModel(model="example2",
  mxData(observed=xdat, type='raw'),
  mxMatrix(values=.75, ncol=1, nrow=1, free=TRUE, name='B'),
  mxAlgebra((filteredDataRow - B) ^ 2, name='rowAlgebra'),
  mxAlgebra(sum(rowResults), name='reduceAlgebra'),
  mxFitFunctionRow(
    rowAlgebra='rowAlgebra',
    reduceAlgebra='reduceAlgebra',
    dimnames=c('a'))
)
bmodOut <- mxRun(bmod)
mxEval(B, model=bmodOut)
mxEval(reduceAlgebra, model=bmodOut)
mxEval(rowResults, model=bmodOut)

```

---

 mxFitFunctionWLS

*Create MxFitFunctionWLS Object*


---

## Description

This function creates a new MxFitFunctionWLS object.

## Usage

```
mxFitFunctionWLS(weights = "ULS")
```

**Arguments**

weights Ignored. Uses weights from [mxData](#)

**Details**

Fit functions are functions for which free parameter values are optimized such that the value of a cost function is minimized. The `mxFitFunctionWLS` function computes the weighted least squares difference between the data and the model-implied expectations for the data based on the free parameters and the expectation function (e.g., [mxExpectationNormal](#) or [mxExpectationRAM](#)) selected for the model.

The 'weights' argument is ignored. Rather the weights are provided in the `mxData` object, often generated by the `mxDataWLS` function.

Usage Notes:

The results of the optimization can be reported using the `summary` function, or accessed directly in the 'output' slot of the resulting model (i.e., `modelName$output`). Components of the output may be referenced using the `Extract` functionality.

**Value**

Returns a new `MxFitFunctionWLS` object. One and only one `MxFitFunctionWLS` object should be included in each model along with an associated [mxExpectationNormal](#) or [mxExpectationRAM](#) object.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

Other fit functions: [mxFitFunctionMultigroup](#), [mxFitFunctionML](#), [mxFitFunctionAlgebra](#), [mxFitFunctionGREML](#), [mxFitFunctionR](#), [mxFitFunctionRow](#)

More information about the OpenMx package may be found [here](#).

**Examples**

```
# Create and fit a model using mxMatrix, mxAlgebra, mxExpectationNormal, and mxFitFunctionWLS

library(OpenMx)

# Simulate some data

x=rnorm(1000, mean=0, sd=1)
y= 0.5*x + rnorm(1000, mean=0, sd=1)
tmpFrame <- data.frame(x, y)
tmpNames <- names(tmpFrame)
wdata <- mxDataWLS(tmpFrame)

# Define the matrices
```

```

S <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(1,0,0,1),
              free=c(TRUE,FALSE,FALSE,TRUE), labels=c("Vx", NA, NA, "Vy"), name = "S")
A <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(0,1,0,0),
              free=c(FALSE,TRUE,FALSE,FALSE), labels=c(NA, "b", NA, NA), name = "A")
I <- mxMatrix(type="Iden", nrow=2, ncol=2, name="I")

# Define the expectation

expCov <- mxAlgebra(solve(I-A) %*% S %*% t(solve(I-A)), name="expCov")
expFunction <- mxExpectationNormal(covariance="expCov", dimnames=tmpNames)

# Choose a fit function

fitFunction <- mxFitFunctionWLS()

# Define the model

tmpModel <- mxModel(model="exampleModel", S, A, I, expCov, expFunction, fitFunction,
                    wdata)

# Fit the model and print a summary

tmpModelOut <- mxRun(tmpModel)
summary(tmpModelOut)

```

---

MxFlatModel-class	<i>MxFlatModel</i>
-------------------	--------------------

---

## Description

This is an internal class and should not be used.

---

mxGenerateData	<i>Generate data based on an MxModel object</i>
----------------	---

---

## Description

This function returns a new (simulated) data set based on the model-implied distribution provided.

## Usage

```

mxGenerateData(model, nrows, returnModel=FALSE, use.miss = TRUE,
              ..., .backend=TRUE, subname=NULL)

```

**Arguments**

<code>model</code>	A <code>data.frame</code> or <code>MxModel</code> object upon which the data are generated.
<code>nrows</code>	Numeric. The number of rows of data to generate.
<code>returnModel</code>	Logical. Return <code>data.frames</code> if <code>FALSE</code> or model populated with new data if <code>TRUE</code> .
<code>use.miss</code>	Logical. Whether to approximate the missingness pattern of the original data.
<code>...</code>	Not used; forces remaining arguments to be specified by name.
<code>.backend</code>	Whether to use the backend to generate data
<code>subname</code>	Submodel name

**Details**

When given a `data.frame` as a model, the model is assumed to be saturated multivariate Gaussian and the expected distribution is obtained using `mxDataWLS`. In this case, the default number of rows is assumed to be the number of rows in the original `data.frame`, but any other number of rows can also be requested.

When given an `MxModel`, the model-implied means and covariance are extracted. It then generates data with the same mean and covariance. Data can be generated based on Normal (`mxExpectationNormal`), RAM (`mxExpectationRAM`), LISREL (`mxExpectationLISREL`), and state space (`mxExpectationStateSpace`) models.

Please note that this function samples data from the model-implied distribution(s); it does not sample from the data object in the model. That is, this function generates new data rather than pulling data that already exist from the model.

Thresholds and ordinal data are implemented by generating continuous data and then using `cut` and `mxFactor` to break the continuous data at the thresholds into an ordered factor.

If the model has definition variables, then a data set must be included in the model object and the number of rows requested must match the number of rows in the model data. In this case the means, covariance, and thresholds are reevaluated for each row of data, potentially creating a different mean, covariance, and threshold structure for every generated row of data.

For state space models (i.e. models with an `mxExpectationStateSpace` or `mxExpectationStateSpaceContinuousTime` expectation), the data are generated based on the autoregressive structure of the model. The rows of data in a state space model are not independent replicates of a stationary process. Rather, they are the result of a latent (possibly non-stationary) autoregressive process. For state space models different rows of data often correspond to different times. As alluded to above, data generation works for discrete time state space models and hybrid continuous-discrete time state space models. The latter have a continuous process that is measured as discrete times.

The `subname` parameter is used to limit data generation to the given submodel. The reason you wouldn't pass the submodel in the `model` argument is that some parts of the submodel might depend on objects in other submodels that are part of the model.

**Value**

A `data.frame`, list of `data.frames`, or model populated with the new data (depending on the `returnModel` parameter). Raw data is always returned even if the original model contained covariance or some other non-raw data.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## Examples

```
#-----
# Create data based on state space model.
require(OpenMx)
nvar <- 5
varnames <- paste("x", 1:nvar, sep="")
ssModel <- mxModel(model="State Space Manual Example",
  mxMatrix("Full", 1, 1, TRUE, .3, name="A"),
  mxMatrix("Zero", 1, 1, name="B"),
  mxMatrix("Full", nvar, 1, TRUE, .6, name="C", dimnames=list(varnames, "F1")),
  mxMatrix("Zero", nvar, 1, name="D"),
  mxMatrix("Diag", 1, 1, FALSE, 1, name="Q"),
  mxMatrix("Diag", nvar, nvar, TRUE, .2, name="R"),
  mxMatrix("Zero", 1, 1, name="x0"),
  mxMatrix("Diag", 1, 1, FALSE, 1, name="P0"),
  mxMatrix("Zero", 1, 1, name="u"),
  mxExpectationStateSpace("A", "B", "C", "D", "Q", "R", "x0", "P0", "u"),
  mxFitFunctionML()
)

ssData <- mxGenerateData(ssModel, 200) # 200 time points

# Add simulated data to model
ssModel <- mxModel(ssModel, mxData(ssData, 'raw'))

# Fit model to simulated data
ssRun <- mxRun(ssModel)

# Compare parameters estimated from random data to
# their true generating values
cbind(Rand = omxGetParameters(ssRun), Gen = omxGetParameters(ssModel))
# Note the parameters should be "close" (up to sampling error)
# to the generating values

#-----
require(OpenMx)
manifests <- paste("x", 1:5, sep="")
latents <- c("G")
factorModel <- mxModel("One Factor",
  type="RAM",
  manifestVars = manifests,
  latentVars = latents,
  mxPath(from=latents, to=manifests, values=.8),
  mxPath(from=manifests, arrows=2, values=.2),
  mxPath(from=latents, arrows=2,
    free=FALSE, values=1.0),
```

```

mxPath(from = 'one', to = manifests))

factorData <- mxGenerateData(factorModel, 100)

factorModel <- mxModel(factorModel,
  mxData(observed=cov(factorData), type="cov",
    numObs=nrow(factorData),
    means = colMeans(factorData)))
factorRun <- mxRun(factorModel)
cbind(Rand=omxGetParameters(factorRun), Gen=omxGetParameters(factorModel))

```

---

mxGetExpected

*Extract the component from a model's expectation*


---

### Description

This function extracts the expected means, covariance, or thresholds from a model.

### Usage

```

mxGetExpected(model, component, defvar.row=1, subname=model$name)
imxGetExpectationComponent(model, component, defvar.row=1, subname=model$name)

```

### Arguments

model	MxModel object from which to extract the expectation component.
component	Character vector. The name(s) of the component(s) to extract. Recognized names are “covariance”, “means”, and “thresholds”.
defvar.row	A row index. Which row to load for definition variables.
subname	Name of the submodel to evaluate.

### Details

The expected means, covariance, or thresholds can be extracted from Normal ([mxExpectationNormal](#)), RAM ([mxExpectationRAM](#)), and LISREL ([mxExpectationLISREL](#)) models. When more than one component is requested, the components will be returned as a list.

If component 'vector' is requested then the non-redundent coefficients of the expected manifest distribution will be returned as a vector.

If component 'standVector' is requested then the same parameter structure as 'vector' is returned, but it is standardized. For Normal expectations the covariances are returned as correlations, the means are returned as zeros, and the thresholds are returned as z-scores. For the thresholds the z-scores are computed by using the model-implied means and variances.

Note that capitalization is ignored for the 'standVector' option, so 'standvector' is also acceptable.



**Value**

See details.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
#-----
require(OpenMx)
manifests <- paste("x", 1:5, sep="")
latents <- c("G")
factorModel <- mxModel("One Factor",
  type="RAM",
  manifestVars = manifests,
  latentVars = latents,
  mxPath(from=latents, to=manifests),
  mxPath(from=manifests, arrows=2),
  mxPath(from=latents, arrows=2,
    free=FALSE, values=1.0),
  mxPath(from = 'one', to = manifests))

mxGetExpected(factorModel, "covariance")
# oops. Starting values indicate a zero covariance matrix.
# Probably should adjust them.
```

---

mxGREMLDataHandler      *Helper Function for Structuring GREML Data*

---

**Description**

This function takes a dataframe or matrix and uses it to setup the 'y' and 'X' matrices for a GREML analysis; this includes trimming out NAs from 'X' and 'y.' The result is a matrix the first column of which is the 'y' vector, and the remaining columns of which constitute 'X.'

**Usage**

```
mxGREMLDataHandler(data, yvars=character(0), Xvars=list(), addOnes=TRUE,
  blockByPheno=TRUE, staggerZeroes=TRUE)
```

**Arguments**

data	Either a dataframe or matrix, with column names, containing the variables to be used as phenotypes and covariates in 'y' and 'X,' respectively.
yvars	Character vector. Each string names a column of the raw dataset, to be used as a phenotype.

<code>Xvars</code>	A list of data column names, specifying the covariates to be used with each phenotype. The list should have the same length as argument <code>yvars</code> .
<code>addOnes</code>	Logical; should lead columns of ones (for the regression intercepts) be adhered to the covariates when assembling the 'X' matrix? Defaults to TRUE.
<code>blockByPheno</code>	Logical; relevant to polyphenotype analyses. If TRUE (default), then the resulting 'y' will contain phenotype #1 for individuals 1 thru $n$ , phenotype #2 for individuals 1 thru $n$ , ... If FALSE, then observations are "blocked by individual", and the resulting 'y' will contain individual #1's scores on phenotypes 1 thru $p$ , individual #2's scores on phenotypes 1 thru $p$ , ... Note that in either case, 'X' will be structured appropriately for 'y.'
<code>staggerZeroes</code>	Logical; relevant to polyphenotype analyses. If TRUE (default), then each phenotype's covariates in 'X' are "staggered," and 'X' is padded out with zeroes. If FALSE, then 'X' is formed simply by stacking the phenotypes' covariates; this requires each phenotype to have the same number of covariates (i.e., each character vector in <code>Xvars</code> must be of the same length). The default (TRUE) is intended for instances where the multiple phenotypes truly are different variables, whereas <code>staggerZeroes=FALSE</code> is intended for instances where the multiple "phenotypes" actually represent multiple observations on the same variable. One example of the latter case is longitudinal data where the multiple "phenotypes" are repeated measures on a single phenotype.

## Details

For a monophenotype analysis (only), argument `Xdata` can be a character vector. In a polyphenotype analysis, if the same covariates are to be used with all phenotypes, then `Xdata` can be a list of length 1.

Note the synergy between the output of `mxGREMLDataHandler()` and arguments `dataset.is.yX` and `casesToDropFromV` to `mxExpectationGREML()`.

If the dataframe or matrix supplied for argument `data` has  $n$  rows, and argument `yvars` is of length  $p$ , then the resulting 'y' and 'X' matrices will have  $np$  rows. Then, if either matrix contains any NA's, the rows containing the NA's are trimmed from both 'X' and 'y' before being returned in the output (in which case they will obviously have fewer than  $np$  rows). Function `mxGREMLDataHandler()` reports which rows of the full-size 'X' and 'y' were trimmed out due to missing observations. These row indices can be provided as argument `casesToDropFromV` to `mxExpectationGREML()`.

## Value

A list with these two components:

<code>yX</code>	Numeric matrix. The first column is the phenotype vector, 'y,' while the remaining columns constitute the 'X' matrix of covariates. If this matrix is used as the raw dataset for a model, then the model's GREML expectation can be constructed with <code>dataset.is.yX=TRUE</code> in <code>mxExpectationGREML()</code> .
<code>casesToDrop</code>	Numeric vector. Contains the indices of the rows of the 'y' and 'X' that were dropped due to containing NA's. Can be provided as argument <code>casesToDropFromV</code> to <code>mxExpectationGREML()</code> .

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

For more information generally concerning GREML analyses, including a complete example, see [mxExpectationGREML\(\)](#). More information about the OpenMx package may be found [here](#).

**Examples**

```
dat <- cbind(rnorm(100),rep(1,100))
colnames(dat) <- c("y","x")
dat[42,1] <- NA
dat[57,2] <- NA
dat2 <- mxGREMLDataHandler(data=dat, yvars="y", Xvars=list("x"),
  addOnes = FALSE)
str(dat2)
```

---

MxInterval-class	<i>MxInterval</i>
------------------	-------------------

---

**Description**

This is an internal class and should not be used directly.

**See Also**

[mxCI](#)

---

mxKalmanScores	<i>Estimate Kalman scores and error covariance matrices</i>
----------------	---

---

**Description**

This function creates the Kalman predicted, Kalman updated, and Rauch-Tung-Striebel smoothed latent state and error covariance estimates for an MxModel object that has an MxExpectationStateSpace object.

**Usage**

```
mxKalmanScores(model, data=NA, frontend=TRUE)
```

**Arguments**

model	An MxModel object with an MxExpectationStateSpace.
data	An optional data.frame or matrix.
frontend	When TRUE, compute score in the frontend, otherwise use the backend.

## Details

This is a helper function that computes the results of the classical Kalman filter. In particular, for every row of data there is a predicted latent score, an error covariance matrix for the predicted latent scores that provides an estimate of the predictions precision, an updated latent score, and an updated error covariance matrix for the updated lated scores. Additionally, the Rauch-Tung-Striebel (RTS) smoothed latent scores and error covariance matrices are returned.

## Value

A list with components `xPredicted`, `PPredicted`, `xUpdated`, `PUpdated`, `xSmoothed`, `PSmoothed`, `m2ll`, and `L`. When using backend scores, this list also has components for `yPredicted` and `SPredicted` which have the same number of time points as the other components but relate to the observed variables instead of the latent variables. The rows of `xPredicted`, `xUpdated`, and `xSmoothed` correspond to different time points. The columns are the different latent variables. The third index of `PPredicted`, `PUpdated`, and `PSmoothed` corresponds to different times. This works nicely with the R default print method for arrays. At each time there is a covariance matrix of the latent variable scores. For all items listed below, the first element goes with the zeroth time point (See example).

**xPredicted** matrix of Kalman predicted scores

**PPredicted** array of Kalman predicted error covariances

**xUpdated** matrix of Kalman updated scores

**PUpdated** array of Kalman updated error covariances

**xSmoothed** matrix of RTS smoothed scores

**PSmoothed** array of RTS smoothed error covariances

**m2ll** minus 2 log likelihood

**L** likelihood, i.e., the multivariate normal probability density

**yPredicted** matrix of Kalman predicted scores for the observed variables, i.e., the predicted means. Only available for backend scores.

**SPredicted** array of Kalman predicted error covariances for the observed variables, i.e., the predicted covariances. Only available for backend scores.

## References

J. Durbin and S.J. Koopman. (2001). *Time Series Analysis by State Space Methods*. Oxford University Press.

R.E. Kalman (1960). A New Approach to Linear Filtering and Prediction Problems. *Basic Engineering*, 82, 35-45.

H.E. Rauch, F. Tung, C.T. Striebel. (1965). Maximum Likelihood Estimates of Linear Dynamic Systems. *American Institute of Aeronautics and Astronautics Journal*, 3, 1445-1450.

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

[mxExpectationStateSpace](#)

**Examples**

```

# Create and fit a model using mxMatrix, mxExpectationStateSpace, and mxFitFunctionML
require(OpenMx)
data(demoOneFactor)
# Use only first 50 rows, for speed of example
data <- demoOneFactor[1:50,]
nvar <- ncol(demoOneFactor)
varnames <- colnames(demoOneFactor)
ssModel <- mxModel(model="State Space Manual Example",
  mxMatrix("Full", 1, 1, TRUE, .3, name="A"),
  mxMatrix("Zero", 1, 1, name="B"),
  mxMatrix("Full", nvar, 1, TRUE, .6, name="C", dimnames=list(varnames, "F1")),
  mxMatrix("Zero", nvar, 1, name="D"),
  mxMatrix("Diag", 1, 1, FALSE, 1, name="Q"),
  mxMatrix("Diag", nvar, nvar, TRUE, .2, name="R"),
  mxMatrix("Zero", 1, 1, name="x0"),
  mxMatrix("Diag", 1, 1, FALSE, 1, name="P0"),
  mxMatrix("Zero", 1, 1, name="u"),
  mxData(observed=data, type="raw"),
  mxExpectationStateSpace("A", "B", "C", "D", "Q", "R", "x0", "P0", "u"),
  mxFitFunctionML()
)
ssRun <- mxRun(ssModel)
summary(ssRun)
# Note the freely estimated Autoregressive parameter (A matrix)
# is near zero as it should be for the independent rows of data
# from the factor model.

ssScores <- mxKalmanScores(ssRun)

cor(cbind(ssScores$xPredicted[,1], ssScores$xUpdated[,1], ssScores$xSmoothed[,1]))
# Because the autoregressive dynamics are near zero, the predicted and updated scores
# correlate minimally, and the updated and smoothed latent state estimates
# are extremely close.

# The first few latent predicted scores
head(ssScores$xPredicted)

# The predicted latent score for time 10
ssScores$xPredicted[10+1,]

# The error covariance of the predicted score at time 10
ssScores$PPredicted[,10+1]

```

**Description**

This is an internal class and should not be used directly.

---

mxLISRELObjective	<i>Create MxLISRELObjective Object</i>
-------------------	--

---

**Description**

This function creates a new MxLISRELObjective object.

**Usage**

```
mxLISRELObjective(LX=NA, LY=NA, BE=NA, GA=NA, PH=NA, PS=NA, TD=NA, TE=NA, TH=NA,
  TX = NA, TY = NA, KA = NA, AL = NA,
  dimnames = NA, thresholds = NA, vector = FALSE, threshnames = dimnames)
```

**Arguments**

LX	An optional character string indicating the name of the 'LX' matrix.
LY	An optional character string indicating the name of the 'LY' matrix.
BE	An optional character string indicating the name of the 'BE' matrix.
GA	An optional character string indicating the name of the 'GA' matrix.
PH	An optional character string indicating the name of the 'PH' matrix.
PS	An optional character string indicating the name of the 'PS' matrix.
TD	An optional character string indicating the name of the 'TD' matrix.
TE	An optional character string indicating the name of the 'TE' matrix.
TH	An optional character string indicating the name of the 'TH' matrix.
TX	An optional character string indicating the name of the 'TX' matrix.
TY	An optional character string indicating the name of the 'TY' matrix.
KA	An optional character string indicating the name of the 'KA' matrix.
AL	An optional character string indicating the name of the 'AL' matrix.
dimnames	An optional character vector that is currently ignored
thresholds	An optional character string indicating the name of the thresholds matrix.
vector	A logical value indicating whether the objective function result is the likelihood vector.
threshnames	An optional character vector to be assigned to the column names of the thresholds matrix.

**Details**

Objective functions are functions for which free parameter values are chosen such that the value of the objective function is minimized. The mxLISRELObjective provides maximum likelihood estimates of free parameters in a model of the covariance of a given MxData object. This model is defined by Linear Structural Relations (LISREL; Jöreskog & Sörbom, 1982, 1996). Arguments 'LX' through 'AL' must refer to MxMatrix objects with the associated properties of their respective matrices in the LISREL modeling approach.

The full LISREL specification has 13 matrices and is sometimes called the extended LISREL model. It is defined by the following equations.

$$\eta = \alpha + B\eta + \Gamma\xi + \zeta$$

$$y = \tau_y + \Lambda_y\eta + \epsilon$$

$$x = \tau_x + \Lambda_x\xi + \delta$$

The table below is provided as a quick reference to the numerous matrices in LISREL models. Note that NX is the number of manifest exogenous (independent) variables, the number of Xs. NY is the number of manifest endogenous (dependent) variables, the number of Ys. NK is the number of latent exogenous variables, the number of Ksis or Xis. NE is the number of latent endogenous variables, the number of etas.

Matrix	Word	Abbreviation	Dimensions	Expression	Description
$\Lambda_x$	Lambda x	LX	NX x NK		Exogenous Factor Loading Matrix
$\Lambda_y$	Lambda y	LY	NY x NE		Endogenous Factor Loading Matrix
$B$	Beta	BE	NE x NE		Regressions of Latent Endogenous Variables Predicted by Latent Exogenous Variables
$\Gamma$	Gamma	GA	NE x NK		Regressions of Latent Exogenous Variables Predicted by Latent Endogenous Variables
$\Phi$	Phi	PH	NK x NK	cov( $\xi$ )	Covariance Matrix of Latent Exogenous Variables
$\Psi$	Psi	PS	NE x NE	cov( $\zeta$ )	Residual Covariance Matrix of Latent Endogenous Variables
$\Theta_\delta$	Theta delta	TD	NX x NX	cov( $\delta$ )	Residual Covariance Matrix of Manifest Exogenous Variables
$\Theta_\epsilon$	Theta epsilon	TE	NY x NY	cov( $\epsilon$ )	Residual Covariance Matrix of Manifest Endogenous Variables
$\Theta_{\delta\epsilon}$	Theta delta epsilon	TH	NX x NY	cov( $\delta, \epsilon$ )	Residual Covariance Matrix of Manifest Exogenous and Manifest Endogenous Variables
$\tau_x$	tau x	TX	NX x 1		Residual Means of Manifest Exogenous Variables
$\tau_y$	tau y	TY	NY x 1		Residual Means of Manifest Endogenous Variables
$\kappa$	kappa	KA	NK x 1	mean( $\xi$ )	Means of Latent Exogenous Variables
$\alpha$	alpha	AL	NE x 1		Residual Means of Latent Endogenous Variables

From the extended LISREL model, several submodels can be defined. Subtypes of the LISREL model are defined by setting some of the arguments of the LISREL objective to NA. Note that because the default values of each LISREL matrix is NA, setting a matrix to NA can be accomplished by simply not giving it any other value.

The first submodel is the LISREL model without means.

$$\eta = B\eta + \Gamma\xi + \zeta$$

$$y = \Lambda_y\eta + \epsilon$$

$$x = \Lambda_x\xi + \delta$$

The LISREL model without means requires 9 matrices: LX, LY, BE, GA, PH, PS, TD, TE, and TH. Hence this LISREL model has TX, TY, KA, and AL as NA. This can be accomplished by leaving these matrices at their default values.

The TX, TY, KA, and AL matrices must be specified if either the mxData type is “cov” or “cor” and a means vector is provided, or if the mxData type is “raw”. Otherwise the TX, TY, KA, and AL matrices are ignored and the model without means is estimated.

A second submodel involves only endogenous variables.

$$\eta = B\eta + \zeta$$

$$y = \Lambda_y\eta + \epsilon$$

The endogenous-only LISREL model requires 4 matrices: LY, BE, PS, and TE. The LX, GA, PH, TD, and TH must be NA in this case. However, means can also be specified, allowing TY and AL if the data are raw or if observed means are provided.

Another submodel involves only exogenous variables.

$$x = \Lambda_x\xi + \delta$$

The exogenous-only model requires 3 matrices: LX, PH, and TD. The LY, BE, GA, PS, TE, and TH matrices must be NA. However, means can also be specified, allowing TX and KA if the data are raw or if observed means are provided.

The model that is run depends on the matrices that are not NA. If all 9 matrices are not NA, then the full model is run. If only the 4 endogenous matrices are not NA, then the endogenous-only model is run. If only the 3 exogenous matrices are not NA, then the exogenous-only model is run. If some endogenous and exogenous matrices are not NA, but not all of them, then appropriate errors are thrown. Means are included in the model whenever their matrices are provided.

The [MxMatrix](#) objects included as arguments may be of any type, but should have the properties described above. The mxLISRELObjective will not return an error for incorrect specification, but incorrect specification will likely lead to estimation problems or errors in the [mxRun](#) function.

Like the [mxRAMObjective](#), the mxLISRELObjective evaluates with respect to an [MxData](#) object. The [MxData](#) object need not be referenced in the mxLISRELObjective function, but must be included in the [MxModel](#) object. mxLISRELObjective requires that the 'type' argument in the associated [MxData](#) object be equal to 'cov', 'cor', or 'raw'.

To evaluate, place MxLISRELObjective objects, the [mxData](#) object for which the expected covariance approximates, referenced [MxAlgebra](#) and [MxMatrix](#) objects, and optional [MxBounds](#) and [MxConstraint](#) objects in an [MxModel](#) object. This model may then be evaluated using the [mxRun](#) function. The results of the optimization can be found in the 'output' slot of the resulting model, and may be obtained using the [mxEval](#) function.

## Value

Returns a new MxLISRELObjective object. MxLISRELObjective objects should be included with models with referenced [MxAlgebra](#), [MxData](#) and [MxMatrix](#) objects.



## References

Jöreskog, K. G. & Sörbom, D. (1996). LISREL 8: User's Reference Guide. Lincolnwood, IL: Scientific Software International.

Jöreskog, K. G. & Sörbom, D. (1982). Recent developments in structural equation modeling. *Journal of Marketing Research*, 19, 404-416.

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## Examples

```
#####-----#####
##### Factor Model
mLX <- mxMatrix("Full", values=c(.5, .6, .8, rep(0, 6), .4, .7, .5),
  name="LX", nrow=6, ncol=2,
  free=c(TRUE,TRUE,TRUE,rep(FALSE, 6),TRUE,TRUE,TRUE))
mTD <- mxMatrix("Diag", values=c(rep(.2, 6)), name="TD", nrow=6, ncol=6,
  free=TRUE)
mPH <- mxMatrix("Symm", values=c(1, .3, 1), name="PH", nrow=2, ncol=2,
  free=c(FALSE, TRUE, FALSE))

# Create a LISREL objective with LX, TD, and PH matrix names
objective <- mxLISRELObjective(LX="LX", TD="TD", PH="PH")

testModel <- mxModel(model="testModel", mLX, mTD, mPH, objective)
```

---

MxListOrNull-class      *An optional list*

---

## Description

An optional list

---

mxMakeNames                      *mxMakeNames*

---

## Description

Adjust a character vector so that it can be used as MxMatrix column or row names. OpenMx is (much) more restrictive than base R's `make.names`.

## Usage

```
mxMakeNames(names, unique = FALSE)
```

**Arguments**

names	a character vector
unique	whether the pass the result through <a href="#">make.unique</a>

**See Also**

[make.names](#)

**Examples**

```
demo <- c("", "103", "data", "foo.bar[3,2]", "+!", "!+")
mxMakeNames(demo, unique=TRUE)
```

---

mxMatrix

*Create MxMatrix Object*


---

**Description**

This function creates a new [MxMatrix](#) object.

**Usage**

```
mxMatrix(type = c('Full', 'Diag', 'Iden', 'Lower',
  'Sdiag', 'Stand', 'Symm', 'Unit', 'Zero'), nrow = NA, ncol = NA,
  free = FALSE, values = NA, labels = NA, lbound = NA,
  ubound = NA, byrow = getOption('mxByrow'), dimnames = NA, name = NA,
  condenseSlots=getOption('mxCondenseMatrixSlots'),
  ..., joinKey=as.character(NA), joinModel=as.character(NA))
```

**Arguments**

type	A character string indicating the matrix type, where type indicates the range of values and equalities in the matrix. Must be one of: 'Diag', 'Full', 'Iden', 'Lower', 'Sdiag', 'Stand', 'Symm', 'Unit', or 'Zero'.
nrow	Integer; the desired number of rows. One or both of 'nrow' and 'ncol' is required when 'values', 'free', 'labels', 'lbound', and 'ubound' arguments are not matrices, depending on the desired <a href="#">MxMatrix</a> type.
ncol	Integer; the desired number of columns. One or both of 'nrow' and 'ncol' is required when 'values', 'free', 'labels', 'lbound', and 'ubound' arguments are not matrices, depending on the desired <a href="#">MxMatrix</a> type.
free	A vector or matrix of logicals for free parameter specification. A single 'TRUE' or 'FALSE' will set all allowable variables to free or fixed, respectively.
values	A vector or matrix of numeric starting values. By default, all values are set to zero.
labels	A vector or matrix of characters for variable label specification.

lbound	A vector or matrix of numeric lower bounds. Default bounds are specified with an NA.
ubound	A vector or matrix of numeric upper bounds. Default bounds are specified with an NA.
byrow	Logical; defaults to value of global <a href="#">option</a> 'mxByRow'. If FALSE (default), the 'values', 'free', 'labels', 'lbound', and 'ubound' matrices are populated by column rather than by row.
dimnames	List. The dimnames attribute for the matrix: a list of length 2 giving the row and column names respectively. An empty list is treated as NULL, and a list of length one as row names. The list can be named, and the list names will be used as names for the dimensions.
name	An optional character string indicating the name of the <a href="#">MxMatrix</a> object.
condenseSlots	Logical; defaults to value of global <a href="#">option</a> 'mxByRow' If TRUE, then the resulting <a href="#">MxMatrix</a> will "condense" its 'labels', 'free', 'lbound', and 'ubound' down to 1x1 matrices if they contain only FALSE ('free') or NA (the other three). If FALSE, those four matrices and the 'values' matrix will all be of equal dimensions.
...	Not used. Forces remaining arguments to be specified by name.
joinKey	The name of the column in current model's raw data that is used as a foreign key to match against the primary key in joinModel's raw data.
joinModel	The name of the model that this matrix joins against.

## Details

The `mxMatrix` function creates [MxMatrix](#) objects, which consist of five matrices and a 'type' argument. The 'values' matrix is made up of numeric elements whose usage and capabilities in other functions are defined by the 'free' matrix. If an element is specified as a fixed parameter in the 'free' matrix, then the element in the 'values' matrix is treated as a constant value and cannot be altered or updated by an objective function when included in an `mxRun` function. If an element is specified as a free parameter in the 'free' matrix, the element in the 'value' matrix is considered a starting value and can be changed by an objective function when included in an `mxRun` function.

Element labels beginning with 'data.' can be used if the [MxMatrix](#) is to be used in an [MxModel](#) object that has a raw dataset (i.e., an [MxData](#) object of type="raw"). Such a label instructs `OpenMx` to use a particular column of the raw dataset to fill in the value of that element. For historical reasons, the variable contained in that column is called a "definition variable." For example, if an [MxMatrix](#) element has the label 'data.x', then `OpenMx` will use the first value of the data column named "x" when evaluating the fitfunction for the first row, and will use the second value of column "x" when evaluating the fitfunction for the second row, and so on. After the call to `mxRun()`, the values for elements labeled with 'data.x' are returned as the value from the first (i.e., first before any automated sorting is done) element of column "x" in the data.

Objects created by the `mxMatrix()` function are of a specific 'type', which specifies the number and location of parameters in the 'labels' matrix and the starting values in the 'values' matrix. Input 'values', 'free', and 'labels' matrices must be of appropriate shape and have appropriate values for the matrix type requested. Nine types of matrices are supported:

'Diag' matrices must be square, and only elements on the principal diagonal may be specified as free parameters or take no

'Full'	matrices may be either rectangular or square, and all elements in the matrix may be freely estimated. This type is the default.
'Iden'	matrices must be square, and consist of no free parameters. Matrices of this type have a value of 1 for all entries on the main diagonal.
'Lower'	matrices must be square, with a value of 0 for all entries in the upper triangle and no free parameters in the upper triangle.
'Sdiag'	matrices must be square, with a value of 0 for all entries in the upper triangle and along the diagonal. No free parameters.
'Symm'	matrices must be square, and elements in the principle diagonal and lower triangular portion of the matrix may be freely estimated.
'Stand'	matrices are symmetric matrices (see 'Symm') with 1's along the main diagonal.
'Unit'	matrices may be either rectangular or square, and contain no free parameters. All elements in matrices of this type are 1.
'Zero'	matrices may be either rectangular or square, and contain no free parameters. All elements in matrices of this type are 0.

When 'type' is 'Lower' or 'Symm', then the arguments to 'free', 'values', 'labels', 'lbound', or 'ubound' may be vectors of length  $N * (N + 1)/2$ , where N is the number of rows and columns of the matrix. When 'type' is 'Sdiag' or 'Stand', then the arguments to 'free', 'values', 'labels', 'lbound', or 'ubound' may be vectors of length  $N * (N - 1)/2$ .

### Value

Returns a new [MxMatrix](#) object, which consists of a 'values' matrix of numeric starting values, a 'free' matrix describing free parameter specification, a 'labels' matrix of labels for the variable names, and 'lbound' and 'ubound' matrices of the lower and upper parameter bounds. This [MxMatrix](#) object can be used as an argument in the [mxAlgebra\(\)](#), [mxBounds\(\)](#), [mxConstraint\(\)](#) and [mxModel\(\)](#) functions.

### References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

### See Also

[MxMatrix](#) for the S4 class created by mxMatrix. More information about the OpenMx package may be found [here](#).

### Examples

```
# Create a 3 x 3 identity matrix

idenMatrix <- mxMatrix(type = "Iden", nrow = 3,
  ncol = 3, name = "I")

# Create a full 4 x 2 matrix from existing
# value matrix with all free parameters

vals <- matrix(1:8, nrow = 4)
fullMatrix <- mxMatrix(type = "Full", values = vals,
  free = TRUE, name = "foo")

# Create a 3 x 3 symmetric matrix with free off-
# diagonal parameters and starting values

symmMatrix <- mxMatrix(type = "Symm", nrow = 3, ncol = 3,
```

```

    free = c(FALSE, TRUE, TRUE, FALSE, TRUE, FALSE),
    values = c(1, .8, .8, 1, .8, 1),
    labels = c(NA, "free1", "free2", NA, "free3", NA),
    name = "bar")

# Create an mxMatrix from a character matrix. All numbers are
# interpreted as fixed and non-numbers are interpreted as free
# parameters.

matrixFromChar <- function(inputm, name=NA) {
  inputmFixed <- suppressWarnings(matrix(
    as.numeric(inputm), nrow = nrow(inputm), ncol = ncol(inputm)))
  inputmCharacter <- inputm
  inputmCharacter[!is.na(inputmFixed)] <- NA
  mxMatrix(nrow=nrow(inputm), ncol=ncol(inputm),
    free=!is.na(inputmCharacter),
    values=inputmFixed,
    labels=inputmCharacter,
    dimnames=dimnames(inputm), name=name)
}

# Demonstrate some of the behavior of the condensed slots
# Create a 3x3 matrix with condensed slots

a <- mxMatrix('Full', 3, 3, values=1, condenseSlots=TRUE)
a@free # at operator returns the stored 1x1 matrix
a$free # dollar operator constructs full matrix for printing

# assignment with the dollar operator
# de-condenses the slots to create the
# full 3x3 matrix
a$free[1,1] <- TRUE
a@free

```

---

MxMatrix-class

*MxMatrix Class*


---

## Description

MxMatrix is a virtual S4 class that comprises the nine types of matrix objects used by OpenMx (see [mxMatrix\(\)](#) for details). An MxMatrix object is a [named entity](#). New instances of this class can be created using the function [mxMatrix\(\)](#). MxMatrix objects may be used as arguments in other functions from the OpenMx package, including [mxAlgebra\(\)](#), [mxConstraint\(\)](#), and [mxModel\(\)](#).

## Objects from the Class

All nine types of object that the class comprises can be created via [mxMatrix\(\)](#).

**Slots**

- name:** Character string; the name of the MxMatrix object. Note that this is the object's "Mx name" (so to speak), which identifies it in OpenMx's internal namespace, rather than the symbol identifying it in R's workspace. Use of MxMatrix objects in an [mxAlgebra](#) or [mxConstraint](#) function requires reference by name.
- values:** Numeric matrix of values. If an element is specified as a fixed parameter in the 'free' matrix, then the element in the 'values' matrix is treated as a constant value and cannot be altered or updated by an objective function when included in an [mxRun\(\)](#) function. If an element is specified as a free parameter in the 'free' matrix, the element in the 'value' matrix is considered a starting value and can be changed by an objective function when included in an [mxRun\(\)](#) function.
- labels:** Matrix of character strings which provides the labels of free and fixed parameters. Fixed parameters with identical labels must have identical values. Free parameters with identical labels impose an equality constraint. The same label cannot be applied to a free parameter and a fixed parameter. A free parameter with the label 'NA' implies a unique free parameter, that cannot be constrained to equal any other free parameter.
- free:** Logical matrix specifying whether each element is free versus fixed. An element is a free parameter if-and-only-if the corresponding value in the 'free' matrix is 'TRUE'. Free parameters are elements of an MxMatrix object whose values may be changed by a fitfunction when that MxMatrix object is included in an [MxModel](#) object and evaluated using the [mxRun\(\)](#) function.
- lbound:** Numeric matrix of lower bounds on free parameters.
- ubound:** Numeric matrix of upper bounds on free parameters.
- .squareBrackets:** Logical matrix; used internally by OpenMx. Identifies which elements have labels with square brackets in them.
- .persist:** Logical; used internally by OpenMx. Governs how [mxRun\(\)](#) handles the MxMatrix object when it is inside the [MxModel](#) being run.
- .condenseSlots:** Logical; used internally by OpenMx. If FALSE, then the matrices in the 'values', 'labels', 'free', 'lbound', and 'ubound' slots are all of equal dimensions. If TRUE, then the last four of those slots will "condense" a matrix consisting entirely of FALSE or NA down to 1x1.
- display:** Character string; used internally by OpenMx when parsing [MxAlgebras](#).
- dependencies:** Integer; used internally by OpenMx when parsing [MxAlgebras](#).

**Methods**

```

$ signature(x = "MxMatrix"): ...
$<- signature(x = "MxMatrix"): ...
[ signature(x = "MxMatrix"): ...
[<- signature(x = "MxMatrix"): ...
dim signature(x = "MxMatrix"): ...
dimnames signature(x = "MxMatrix"): ...
dimnames<- signature(x = "MxMatrix"): ...
length signature(x = "MxMatrix"): ...
names signature(x = "MxMatrix"): ...

```

```

ncol signature(x = "MxMatrix"): ...
nrow signature(x = "MxMatrix"): ...
print signature(x = "MxMatrix"): ...
show signature(object = "MxMatrix"): ...

```

Note that some methods are documented separately (see below, under "See Also").

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

`mxMatrix()` for creating MxMatrix objects. Note that functions `mxCreateMatrix()`, `mxDeparse()`, `mxSquareMatrix()`, `mxSymmetricMatrix()`, and `mxVerifyMatrix()` are separately documented methods for this class. More information about the OpenMx package may be found [here](#).

## Examples

```
showClass("MxMatrix")
```

---

 mxMI

*Estimate Modification Indices for MxModel Objects*

---

## Description

This function estimates the change in fit function value resulting from freeing currently fixed parameters.

## Usage

```
mxMI(model, matrices=NA, full=TRUE)
```

## Arguments

<code>model</code>	An MxModel for which modification indices are desired.
<code>matrices</code>	Character vector. The names of the matrices in which to search for modification
<code>full</code>	Logical. Whether or not to return the full modification index in addition to the restricted.

## Details

Modification indices provide an estimate of how much the fit function value would change if a parameter that is currently fixed was instead freely estimated. There are two versions of this estimate: a restricted version and an full version. The restricted version is reported as the MI and is much faster to compute. The full version is reported as MI.Full. The full version accounts for the *total* change in fit function value resulting from the newly freed parameter. The restricted version only accounts for the change in the fit function due to the movement of the new free parameter. In particular, the restricted version does not account for the change in fit function value due to the other free parameters moving in response to the new parameter.

The algorithm respects fixed parameter labels. That is, when a fixed parameter has a label and occurs in more than one spot, then that fixed parameter is freed in all locations in which it occurs to evaluate the modification index for that fixed parameter.

When the fit function is in minus two log likelihood units (e.g. `mxFitFunctionML`), then the MI will be approximately chi squared distributed with 1 degree of freedom. Using a p-value of 0.01 has been suggested. Hence, a MI greater than  $qchisq(p=1-0.01, df=1)$ , or 6.63, is suggestive of a modification.

Users should be cautious in their use of modification indices. If a model was created with the aid of MIs, then it should *always* be reported. *Do not pretend that you have a theoretical reason for part of a model that was put there because it was suggested by a modification index. This is fraud.* When using modification indices there are two options for best practices. First, you can report the analyses as exploratory. Document all the explorations that you did, and know that your results may or may not generalize. Second, you can use cross-validation. Reserve part of your data for exploration, and use the remaining data to test if the exploratory model generalizes to new data.

## Value

A named list with components

**MI** The restricted modification index.

**MI.Full** The full modification index.

**plusOneParamModels** A list of models with one additional free parameter

## References

Sörbom, D. (1989). Model Modification. *Psychometrika*, 54, 371-384.

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## Examples

```
# Create a model
require(OpenMx)
data(demoOneFactor)
manifests <- names(demoOneFactor)
latents <- c("G")
factorModel <- mxModel("One Factor",
  type="RAM",
  manifestVars = manifests,
  latentVars = latents,
```



```

    mxPath(from=latents, to=manifests),
    mxPath(from=manifests, arrows=2),
    mxPath(from=latents, arrows=2,
           free=FALSE, values=1.0),
    mxPath(from = 'one', to = manifests),
    mxData(observed=cov(demoOneFactor), type="cov", numObs=500,
           means = colMeans(demoOneFactor)))
#No SEs for speed
factorModel <- mxOption(factorModel, 'Standard Errors', 'No')
factorRun <- mxRun(factorModel)

# See if it should be modified
# Notes
# Using full=FALSE for faster performance
# Using matrices= 'A' and 'S' to not get MIs for
#   the F matrix which is always fixed.
fim <- mxMI(factorRun, matrices=c('A', 'S'), full=FALSE)
round(fim$MI, 3)
plot(fim$MI, ylim=c(0, 10))
abline(h=qchisq(p=1-0.01, df=1)) # line of "significance"

```

---

mxMLObjective

*DEPRECATED: Create MxMLObjective Object*


---

## Description

**WARNING:** Objective functions have been deprecated as of OpenMx 2.0.

Please use `mxExpectationNormal()` and `mxFitFunctionML()` instead. As a temporary workaround, `mxMLObjective` returns a list containing an `MxExpectationNormal` object and an `MxFitFunctionML` object.

`mxMLObjective(covariance, means = NA, dimnames = NA, thresholds = NA)` All occurrences of `mxMLObjective(covariance, means = NA, dimnames = NA, thresholds = NA)`

Should be changed to

`mxExpectationNormal(covariance, means = NA, dimnames = NA, thresholds = NA, threshnames = dimnames)` `mxFitFunctionML(vector = FALSE)`

## Arguments

<code>covariance</code>	A character string indicating the name of the expected covariance algebra.
<code>means</code>	An optional character string indicating the name of the expected means algebra.
<code>dimnames</code>	An optional character vector to be assigned to the dimnames of the covariance and means algebras.
<code>thresholds</code>	An optional character string indicating the name of the thresholds matrix.

## Details

NOTE: THIS DESCRIPTION IS DEPRECATED. Please change to using [mxExpectationNormal](#) and [mxFitFunctionML](#) as shown in the example below.

Objective functions are functions for which free parameter values are chosen such that the value of the objective function is minimized. The mxMLObjective function uses full-information maximum likelihood to provide maximum likelihood estimates of free parameters in the algebra defined by the 'covariance' argument given the covariance of an [MxData](#) object. The 'covariance' argument takes an [MxAlgebra](#) object, which defines the expected covariance of an associated [MxData](#) object. The 'dimnames' arguments takes an optional character vector. If this argument is not a single NA, then this vector be assigned to be the dimnames of the means vector, and the row and columns dimnames of the covariance matrix.

mxMLObjective evaluates with respect to an [MxData](#) object. The [MxData](#) object need not be referenced in the mxMLObjective function, but must be included in the [MxModel](#) object. mxMLObjective requires that the 'type' argument in the associated [MxData](#) object be equal to 'cov' or 'cov'. The 'covariance' argument of this function evaluates with respect to the 'matrix' argument of the associated [MxData](#) object, while the 'means' argument of this function evaluates with respect to the 'vector' argument of the associated [MxData](#) object. The 'means' and 'vector' arguments are optional in both functions. If the 'means' argument is not specified (NA), the optional 'vector' argument of the [MxData](#) object is ignored. If the 'means' argument is specified, the associated [MxData](#) object should specify a 'means' argument of equivalent dimension as the 'means' algebra.

dimnames must be supplied where the matrices referenced by the covariance and means algebras are not themselves labeled. Failure to do so leads to an error noting that the covariance or means matrix associated with the ML objective does not contain dimnames.

To evaluate, place MxMLObjective objects, the [mxData](#) object for which the expected covariance approximates, referenced [MxAlgebra](#) and [MxMatrix](#) objects, and optional [MxBounds](#) and [MxConstraint](#) objects in an [MxModel](#) object. This model may then be evaluated using the [mxRun](#) function. The results of the optimization can be found in the 'output' slot of the resulting model, or using the [mxEval](#) function.

## Value

Returns a list containing an [MxExpectationNormal](#) object and an [MxFitFunctionML](#) object.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## Examples

```
# Create and fit a model using mxMatrix, mxAlgebra, mxExpectationNormal, and mxFitFunctionML

library(OpenMx)

# Simulate some data

x=rnorm(1000, mean=0, sd=1)
y= 0.5*x + rnorm(1000, mean=0, sd=1)
```

```

tmpFrame <- data.frame(x, y)
tmpNames <- names(tmpFrame)

# Define the matrices

S <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(1,0,0,1),
              free=c(TRUE,FALSE,FALSE,TRUE), labels=c("Vx", NA, NA, "Vy"), name = "S")
A <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(0,1,0,0),
              free=c(FALSE,TRUE,FALSE,FALSE), labels=c(NA, "b", NA, NA), name = "A")
I <- mxMatrix(type="Iden", nrow=2, ncol=2, name="I")

# Define the expectation

expCov <- mxAlgebra(solve(I-A) %*% S %*% t(solve(I-A)), name="expCov")
expFunction <- mxExpectationNormal(covariance="expCov", dimnames=tmpNames)

# Choose a fit function

fitFunction <- mxFitFunctionML()

# Define the model

tmpModel <- mxModel(model="exampleModel", S, A, I, expCov, expFunction, fitFunction,
                    mxData(observed=cov(tmpFrame), type="cov", numObs=dim(tmpFrame)[1]))

# Fit the model and print a summary

tmpModelOut <- mxRun(tmpModel)
summary(tmpModelOut)

```

---

mxModel

*Create MxModel Object*


---

## Description

This function creates a new [MxModel](#) object.

## Usage

```

mxModel(model = NA, ..., manifestVars = NA, latentVars = NA,
        remove = FALSE, independent = NA, type = NA, name = NA)

```

## Arguments

**model** This argument is either an [MxModel](#) object or a string. If 'model' is an Mx-Model object, then all elements of that model are placed in the resulting Mx-Model object. If 'model' is a string, then a new model is created with the string as its name. If 'model' is either unspecified or 'model' is a named entity, data source, or MxPath object, then a new model is created.

...	An arbitrary number of <code>mxMatrix</code> , <code>mxPath</code> , <code>mxData</code> , and other functions such as <code>mxConstraints</code> and <code>mxCI</code> . These will all be added or removed from the model as specified in the 'model' argument, based on the 'remove' argument.
<code>manifestVars</code>	For RAM-type models, A list of manifest variables to be included in the model.
<code>latentVars</code>	For RAM-type models, A list of latent variables to be included in the model.
<code>remove</code>	logical. If TRUE, elements listed in this statement are removed from the original model. If FALSE, elements listed in this statement are added to the original model.
<code>independent</code>	logical. If TRUE then the model is evaluated independently of other models.
<code>type</code>	character vector. The model type to assign to this model. Defaults to <code>options("mxDefaultType")</code> . See below for valid types
<code>name</code>	An optional character vector indicating the name of the object.

### Details

The `mxModel` function is used to create `MxModel` objects. Objects created by this function may be new, or may be modified versions of existing `MxModel` objects. By default a new `MxModel` object will be created: To create a modified version of an existing `MxModel` object, include this model in the 'model' argument.

Other [named-entities](#) may be added as arguments to the `mxModel` function, which are then added to or removed from the model specified in the 'model' argument. Other functions you can use to add objects to the model to this way are `mxCI`, `mxAlgebra`, `mxBounds`, `mxConstraint`, `mxData`, and `mxMatrix` objects, as well as objective functions. You can also include `MxModel` objects as sub-models of the output model, and may be estimated separately or jointly depending on shared parameters and the 'independent' flag discussed below. Only one `MxData` object and one objective function may be included per model, but there are no restrictions on the number of other [named-entities](#) included in an `mxModel` statement.

All other arguments must be named (i.e. 'latentVars = names'), or they will be interpreted as elements of the ellipsis list. The 'manifestVars' and 'latentVars' arguments specify the names of the manifest and latent variables, respectively, for use with the `mxPath` function. The 'remove' argument may be used when `mxModel` is used to create a modified version of an existing `MxMatrix` object. When 'remove' is set to TRUE, the listed objects are removed from the model specified in the 'model' argument. When 'remove' is set to FALSE, the listed objects are added to the model specified in the 'model' argument.

Model independence may be specified with the 'independent' argument. If a model is independent ('independent = TRUE'), then the parameters of this model are not shared with any other model. An independent model may be estimated with no dependency on any other model. If a model is not independent ('independent = FALSE'), then this model shares parameters with one or more other models such that these models must be jointly estimated. These dependent models must be entered as arguments in another model, so that they are simultaneously optimized.

The model type is determined by a character vector supplied to the 'type' argument. The type of a model is a dynamic property, ie. it is allowed to change during the lifetime of the model. To see a list of available types, use the `mxTypes` command. When a new model is created and no type is specified, the type specified by `options("mxDefaultType")` is used.

To be estimated, `MxModel` objects must include objective functions as arguments (`mxAlgebraObjective`, `mxFIMLObjective`, `mxMLObjective` or `mxRAMObjective`) and executed using the `mxRun`

function. When [MxData](#) objects are included in models, the 'type' argument of these objects may require or exclude certain objective functions, or set an objective function as default.

[Named entities](#) in [MxModel](#) objects may be viewed and referenced by name using the \$ symbol. For instance, for an [MxModel](#) named "yourModel" containing an [MxMatrix](#) named "yourMatrix", the contents of "yourMatrix" can be accessed as `yourModel$yourMatrix`. Slots (i.e., matrices, algebras, etc.) in an [mxMatrix](#) may also be referenced with the \$ symbol (e.g., `yourModel$matrices` or `yourModel$algebras`). See the documentation for [Classes](#) and the examples in [Classes](#) for more information.

## Value

Returns a new [MxModel](#) object. [MxModel](#) objects must include an objective function to be used as arguments in [mxRun](#) functions.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

See [mxCI](#) for information about adding Confidence Interval calculations to a model. See [mxPath](#) for information about adding paths to RAM-type models. See [mxMatrix](#) for information about adding matrices to models. See [mxData](#) for specifying the data a model is to be evaluated against. See [MxModel](#) for the S4 class created by [mxMatrix](#). Many advanced options can be set via [mxOption](#) (such as calculating the Hessian). More information about the OpenMx package may be found [here](#).

## Examples

```
library(OpenMx)

# At the simplest, you can create an empty model,
# placing it in an object, and add to it later
emptyModel <- mxModel(model="IAmEmpty")

# Create a model named 'firstdraft' with one matrix 'A'
firstModel <- mxModel(model='firstdraft',
                      mxMatrix(type='Full', nrow = 3, ncol = 3, name = "A"))

# Update 'firstdraft', and rename the model 'finaldraft'
finalModel <- mxModel(model=firstModel,
                      mxMatrix(type='Symm', nrow = 3, ncol = 3, name = "S"),
                      mxMatrix(type='Iden', nrow = 3, name = "F"),
                      name= "finaldraft")

# Add data to the model from an existing data frame in object 'data'
data(twinData) # load some data
finalModel <- mxModel(model=finalModel, mxData(twinData, type='raw'))

# Two ways to view the matrix named "A" in MxModel object 'model'
```

```

finalModel$A

finalModel$matrices$A

# A working example using OpenMx Path Syntax
data(HS.ability.data) # load the data

# The manifest variables loading on each proposed latent variable
Spatial <- c("visual", "cubes", "paper")
Verbal <- c("general", "paragrap", "sentence")
Math <- c("numeric", "series", "arithmet")

latents <- c("vis", "math", "text")
manifests <- c(Spatial, Math, Verbal)

HSMModel <- mxModel(model="Holzinger_and_Swineford_1939", type="RAM",
  manifestVars = manifests, # list the measured variables (boxes)
  latentVars = latents, # list the latent variables (circles)
  # factor loadings from latents to manifests
  mxPath(from="vis", to=Spatial),# factor loadings
  mxPath(from="math", to=Math), # factor loadings
  mxPath(from="text", to=Verbal), # factor loadings

  # Allow latent variables to covary
  mxPath(from="vis" , to="math", arrows=2, free=TRUE),
  mxPath(from="vis" , to="text", arrows=2, free=TRUE),
  mxPath(from="math", to="text", arrows=2, free=TRUE),

  # Allow latent variables to have variance
  mxPath(from=latents, arrows=2, free=FALSE, values=1.0),
  # Manifest have residual variance
  mxPath(from=manifests, arrows=2),
  # the data to be analysed
  mxData(cov(HS.ability.data[,manifests]), type = "cov", numObs = 301))

fitModel <- mxRun(HSMModel) # run the model
summary(fitModel) # examine the output: Fit statistics and path loadings

```

---

MxModel-class

*MxModel Class*


---

## Description

MxModel is an S4 class. An MxModel object is a [named entity](#).

## Details

The 'matrices' slot contains a list of the [MxMatrix](#) objects included in the model. These objects are listed by name. Two objects may not share the same name. If a new [MxMatrix](#) is added to

an MxModel object with the same name as an [MxMatrix](#) object in that model, the added version replaces the previous version. There is no imposed limit on the number of [MxMatrix](#) objects that may be added here.

The ‘algebras’ slot contains a list of the [MxAlgebra](#) objects included in the model. These objects are listed by name. Two objects may not share the same name. If a new [MxAlgebra](#) is added to an MxModel object with the same name as an [MxAlgebra](#) object in that model, the added version replaces the previous version. All [MxMatrix](#) objects referenced in the included [MxAlgebra](#) objects must be included in the ‘matrices’ slot prior to estimation. There is no imposed limit on the number of [MxAlgebra](#) objects that may be added here.

The ‘constraints’ slot contains a list of the [MxConstraint](#) objects included in the model. These objects are listed by name. Two objects may not share the same name. If a new [MxConstraint](#) is added to an MxModel object with the same name as an [MxConstraint](#) object in that model, the added version replaces the previous version. All [MxMatrix](#) objects referenced in the included [MxConstraint](#) objects must be included in the ‘matrices’ slot prior to estimation. There is no imposed limit on the number of [MxConstraint](#) objects that may be added here.

The ‘intervals’ slot contains a list of the confidence intervals requested by included [MxCI](#) objects. These objects are listed by the free parameters, [MxMatrices](#) and [MxAlgebras](#) referenced in the [MxCI](#) objects, not the list of [MxCI](#) objects themselves. If a new [MxCI](#) object is added to an MxModel object referencing one or more free parameters [MxMatrices](#) or [MxAlgebras](#) previously listed in the ‘intervals’ slot, the new confidence interval(s) replace the existing ones. All listed confidence intervals must refer to free parameters [MxMatrices](#) or [MxAlgebras](#) in the model.

The ‘latentVars’ slot contains a list of latent variable names, which may be referenced by [MxPath](#) objects. This slot defaults to ‘NA’, and is only used when the [mxPath](#) function is used.

The ‘manifestVars’ slot contains a list of latent variable names, which may be referenced by [MxPath](#) objects. This slot defaults to ‘NA’, and is only used when the [mxPath](#) function is used.

The ‘data’ slot contains an [MxData](#) object. This slot must be filled prior to execution when a fitfunction referencing data is used. Only one [MxData](#) object may be included per model, but submodels may have their own data in their own ‘data’ slots. If an [MxData](#) object is added to an MxModel which already contains an [MxData](#) object, the new object replaces the existing one.

The ‘submodels’ slot contains references to all of the MxModel objects included as submodels of this MxModel object. Models held as arguments in other models are considered to be submodels. These objects are listed by name. Two objects may not share the same name. If a new submodel is added to an MxModel object with the same name as an existing submodel, the added version replaces the previous version. When a model containing other models is executed using [mxRun](#), all included submodels are executed as well. If the submodels are dependent on one another, they are treated as one larger model for purposes of estimation.

The ‘independent’ slot contains a logical value indicating whether or not the model is independent. If a model is independent (independent=TRUE), then the parameters of this model are not shared with any other model. An independent model may be estimated with no dependency on any other model. If a model is not independent (independent=FALSE), then this model shares parameters with one or more other models such that these models must be jointly estimated. These dependent models must be entered as submodels of another MxModel objects, so that they are simultaneously optimized.

The ‘options’ slot contains a list of options for the model. The name of each entry in the list is the option name to be used at runtime. The values in this list are the values of the optimizer options. The standard interface for updating options is through the [mxOption](#) function.

The 'output' slot contains a list of output added to the model by the `mxRun` function. Output includes parameter estimates, optimization information, model fit, and other information. If a model has not been optimized using the `mxRun` function, the 'output' slot will be 'NULL'.

**Named entities** in `MxModel` objects may be viewed and referenced by name using the \$ symbol. For instance, for an `MxModel` named "yourModel" containing an `MxMatrix` named "yourMatrix", the contents of "yourMatrix" can be accessed as `yourModel$yourMatrix`. Slots (i.e., matrices, algebras, etc.) in an `mxMatrix` may also be referenced with the \$ symbol (e.g., `yourModel$matrices` or `yourModel$algebras`). See the documentation for [Classes](#) and the examples in `mxModel` for more information.

### Objects from the Class

Objects can be created by calls of the form `mxModel()`.

### Slots

**name:** Character string. The name of the model object.

**matrices:** List of the model's `MxMatrix` objects.

**algebras:** List of the model's `MxAlgebra` objects.

**constraints:** List of the model's `MxConstraint` objects.

**intervals:** List of the model's `MxInterval` objects, requested via `mxCI()`.

**latentVars:** "Latent variables;" object of class "MxCharOrList".

**manifestVars:** "Manifest variables;" object of class "MxCharOrList".

**data:** Object of class `MxData`.

**submodels:** List of `MxModel` objects.

**expectation:** Object of class `MxExpectation`; dictates the model's specification.

**fitfunction:** Object of class `MxFitFunction`; dictates the cost function to be minimized when fitting the model.

**compute:** Object of class `MxCompute`—the model's compute plan, which contains instructions on what the model is to compute and how to do so.

**independent:** Logical; is the model to be run independently from other submodels?

**options:** List of model-specific options, set by `mxOption()`.

**output:** List of model output produced during a call to `mxRun()`.

**runstate:** List produced by `mxRun()`, which contains the pre-run state of the model object.

**.newobjects:** Logical; for internal use.

**.resetdata:** Logical; for internal use.

**.wasRun:** Logical; for internal use.

**.modifiedSinceRun:** Logical; for internal use.

**.version:** Object of class "package\_version"; for internal use.



## Methods

`$` signature(x = "MxModel"): Accessor. Accesses slots by slot-name. Also accesses constituent [named entities](#), by name.

`$<-` signature(x = "MxModel"): Assignment. Generally, this method will not allow the user to make unsafe changes to the MxModel object.

`[[` signature(x = "MxModel"): Accessor for constituent [named entities](#).

`[[<-` signature(x = "MxModel"): Assignment for a [named entity](#).

`names` signature(x = "MxModel"): Returns names of slots and [named entities](#).

`print` signature(x = "MxModel"): "Print" method.

`show` signature(object = "MxModel"): "Show" method.

Note that `imxInitModel()`, `imxModelBuilder()`, `imxTypeName()`, and `imxVerifyModel()` are separately documented methods for class "MxModel".

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

[mxModel](#) for creating MxModel objects. More information about the OpenMx package may be found [here](#).

## Examples

```
showClass("MxModel")
```

---

 mxModelAverage

---

*Information-Theoretic Model-Averaging and Multimodel Inference*


---

## Description

`omxAkaikeWeights()` orders a list of [MxModels](#) (hereinafter, the "candidate set" of models) from best to worst AIC, reports their Akaike weights, and indicates which are in the confidence set for best-approximating model. `mxModelAverage()` calls `omxAkaikeWeights()` and includes its output, and also reports model-average point estimates and (if requested) their standard errors.

## Usage

```
mxModelAverage(reference=character(0), models=list(),
  include=c("onlyFree","all"), SE=NULL, refAsBlock=FALSE, covariances=list(),
  type=c("AIC","AICc"), conf.level=0.95)
```

```
omxAkaikeWeights(models=list(), type=c("AIC","AICc"), conf.level=0.95)
```

**Arguments**

reference	Vector of character strings referring to <a href="#">parameters</a> , <a href="#">MxMatrices</a> , or <a href="#">MxAlgebras</a> for which model-average estimates are to be computed. Defaults to NULL. If a zero-length value is provided, only the output of <code>omxAkaikeWeights()</code> is returned, with a warning.
models	The candidate set of models: a list of at least two <a href="#">MxModel</a> objects, each of which must be uniquely identified by the value of its name slot. Defaults to an empty list.
include	Character string, either "onlyFree" (default) or "all". When calculating model-average estimates for a given reference quantity, should all the MxModels in the candidate set be included in the calculations, or only those in which the quantity is freely estimated? See below, under "Details," for additional information.
SE	Logical; should standard errors be reported for the model-average point estimates? Defaults to NULL, in which case standard errors are reported if argument <code>include="onlyFree"</code> , and not reported otherwise.
refAsBlock	Logical. If FALSE (default), <code>mxModelAverage()</code> will include a matrix of model-conditional sampling variances for the reference quantities in its output, and model-average results may be based on different subsets of the candidate set if <code>include="onlyFree"</code> . If TRUE, <code>mxModelAverage()</code> will instead include a joint sampling covariance matrix for all reference quantities, and will throw an error if <code>include="onlyFree"</code> and if it is not the case that all reference quantities are freely estimated in all models in the candidate set.
covariances	Optional list of repeated-sampling covariance matrices of free parameter estimates (possibly from bootstrapping or the sandwich estimator); defaults to an empty list. A non-empty list must either be of the same length as <code>models</code> , or have named elements corresponding to names of MxModels in the candidate set. See below, under "Details," for additional information.
type	Character string specifying which information criterion to use: either "AIC" for the ordinary AIC (default), or "AICc" for Hurvich & Tsai's (1989) sample-size corrected AIC.
conf.level	Numeric proportion specifying the desired coverage probability of the confidence set for best-approximating model among the candidate set (Burnham & Anderson, 2002). Defaults to 0.95.

**Details**

If statistical inferences (hypothesis tests and confidence intervals) are the motivation for calculating model-average point estimates and their standard errors, then `include="onlyFree"` (the default) is recommended. Note that, if models in which a quantity is held fixed are included in calculating the quantity's model-average estimate, then that estimate cannot even asymptotically be normally distributed (Bartels, 1997).

If argument `covariances` is non-empty, then either it must be of the same length as argument `models`, or all of its elements must be named after an MxModel in `models` (an MxModel's name is the character string in its name slot). If `covariances` is of the same length as `models` but lacks element names, `mxModelAverage()` will assume that they are ordered so that the first element of

covariances is to be used with the first MxModel, the second element is to be used with the second MxModel, and so on. Otherwise, `mxModelAverage()` assigns the elements of `covariances` to the MxModels by matching element names to MxModel names. If `covariances` doesn't provide a covariance matrix for a given MxModel—perhaps because it is empty, or only provides matrices for a nonempty proper subset of the candidate set—`mxModelAverage()` will fall back to its default behavior of calculating a covariance matrix from the Hessian matrix in the MxModel's output slot. If a covariance matrix cannot be thus calculated and `SE=TRUE`, `SE` is coerced to `FALSE`, with a warning.

The matrices in `covariances` must have complete row and column names, equal to the free parameter labels of the corresponding MxModel. These names indicate to which free parameter a given row or column corresponds.

## Value

`omxAkaikeWeights()` returns a dataframe, with one row for each element of `models`. The rows are sorted by their MxModel's AIC (or AICc), from best to worst. The dataframe has five columns:

1. "model": Character string. The name of the MxModel.
2. "AIC" or "AICc": Numeric. The MxModel's AIC or AICc.
3. "delta": Numeric. The MxModel's AIC (or AICc) minus the best (smallest) AIC (or AICc) in the candidate set.
4. "AkaikeWeight": Numeric. The MxModel's Akaike weight. This column will sum to unity.
5. "inConfidenceSet": Character. Will contain an asterisk if the MxModel is in the confidence set for best-approximating model.

The dataframe also has an attribute, "unsortedModelNames", which contains the names of the MxModels in the same order as they appear in `models` (i.e., without sorting them by their AIC).

If a zero-length value is provided for argument `reference`, then `mxModelAverage()` returns only the output of `omxAkaikeWeights()`, with a warning. Otherwise, for the default values of its arguments, `mxModelAverage()` returns a list with four elements:

1. "Model-Average Estimates": A numeric matrix with one row for each distinct quantity specified by `reference`, and as many as two columns. Its rows are named for the corresponding reference quantities. Its first column, "Estimate", contains the model-average point estimates. If standard errors are being calculated, then its second column, "SE", contains the "model-unconditional" standard errors of the model-average point estimates. Otherwise, there is no second column.
2. "Model-wise Estimates": A numeric matrix with one row for each distinct quantity specified by `reference` (indicated by row name), and one column for each MxModel (indicated by column name). Each element is an estimate of the given reference quantity, from the given MxModel. Quantities that cannot be evaluated for a given MxModel are reported as NA.
3. "Model-wise Sampling Variances": A numeric matrix just like the one in list element 2, except that its elements are the estimated sampling variances of the corresponding model-conditional point estimates in list element 2. Variances for fixed quantities are reported as 0 if `include="all"`, and as NA if `include="onlyFree"`; however, if no covariance matrix is available for a model, all of that model's sampling variances will be reported as NA.
4. "Akaike-Weights Table": The output from `omxAkaikeWeights()`.

If `refAsBlock=TRUE`, list element 3 will instead contain be named "Joint Covariance Matrix", and if `SE=TRUE`, it will contain the joint sampling covariance matrix for the model-average point estimates.

### Note

The "best-approximating model" is defined as the model that truly ("in the population," so to speak) has the smallest Kullback-Leibler divergence from full reality, among the models in the candidate set (Burnham & Anderson, 2002).

A model's Akaike weight is interpretable as the relative weight-of-evidence for that model being the best-approximating model, given the observed data and the candidate set. It has a Bayesian interpretation as the posterior probability that the given model is the best-approximating model in the candidate set, assuming a "savvy" prior probability that depends upon sample size and the number of free parameters in the model (Burnham & Anderson, 2002).

The confidence set for best-approximating model serves to reflect sampling error in the AICs. When fitting the candidate set to data over repeated sampling, the confidence set is expected to contain the best-approximating model with probability equal to its confidence level.

The sampling variances and covariances of the model-average point estimates are calculated from Equations (4) and (5) in Burnham & Anderson (2004). The standard errors reported by `mxModelAverage()` are the square roots of those sampling variances.

For an example of model-averaging and multimodel inference applied to structural equation modeling using OpenMx v1.3 (i.e., well before the functions documented here were implemented), see Kirkpatrick, McGue, & Iacono (2015).

### References

- Bartels, L. M. (1997). Specification uncertainty and model averaging. *American Journal of Political Science*, 41(2), 641-674.
- Burnham, K. P., & Anderson, D. R. (2002). *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach (2nd ed.)*. New York: Springer.
- Burnham, K. P., & Anderson, D. R. (2004). Multimodel inference: Understanding AIC and BIC in model selection. *Sociological Methods & Research*, 33(2), 261-304. doi:10.1177/0049124104268644
- Hurvich, C. M., & Tsai, C-L. (1989). Regression and time series model selection in small samples. *Biometrika*, 76(2), 297-307.
- Kirkpatrick, R. M., McGue, M., & Iacono, W. G. (2015). Replication of a gene-environment interaction via multimodel inference: Additive-genetic variance in adolescents' general cognitive ability increases with family-of-origin socioeconomic status. *Behavior Genetics*, 45, 200-214.

### See Also

[mxCompare\(\)](#)

### Examples

```
require(OpenMx)
data(demoOneFactor)
factorModel1 <- mxModel(
```

```

"OneFactor1",
mxMatrix(
"Full", 5, 1, values=0.8,
labels=paste("a",1:5,sep=""),
free=TRUE, name="A"),
mxMatrix(
"Full", 5, 1, values=1,
labels=paste("u",1:5,sep=""),
free=TRUE, name="Udiag"),
mxMatrix(
"Symm", 1, 1, values=1,
free=FALSE, name="L"),
mxAlgebra(vec2diag(Udiag),name="U"),
mxAlgebra(A %*% L %*% t(A) + U, name="R"),
mxExpectationNormal(
covariance = "R",
dimnames = names(demoOneFactor)),
mxFitFunctionML(),
mxData(cov(demoOneFactor), type="cov", numObs=500)
factorFit1 <- mxRun(factorModel1)
#Constrain unique variances equal:
factorModel2 <- omxSetParameters(
model=factorModel1,labels=paste("u",1:5,sep=""),
newlabels="u",name="OneFactor2")
factorFit2 <- mxRun(factorModel2)
omxAkaikeWeights(models=list(factorFit1,factorFit2))
## Not run:
mxModelAverage(
reference=c("A","Udiag"), include="all",
models=list(factorFit1,factorFit2))

## End(Not run)

```

---

mxNormalQuantiles

*mxNormalQuantiles*


---

## Description

Get quantiles from a normal distribution

## Usage

```
mxNormalQuantiles(nBreaks, mean = 0, sd = 1)
```

## Arguments

nBreaks	the number of thresholds, or a vector of the number of thresholds
mean	the mean of the underlying normal distribution
sd	the standard deviation of the underlying normal distribution

**Value**

a vector of quantiles

**Examples**

```
mxNormalQuantiles(3)
mxNormalQuantiles(3, mean=7)
mxNormalQuantiles(2, mean=1, sd=3)
```

---

 mxOption

*Set or Clear an Optimizer Option*


---

**Description**

The function sets, shows, or clears an option that is specific to the optimizer in the back-end.

**Usage**

```
mxOption(model, key, value, reset = FALSE)
```

**Arguments**

model	An <a href="#">MxModel</a> object or NULL
key	The name of the option.
value	The value of the option.
reset	If TRUE then reset all options to their defaults.

**Details**

mxOption is used to set, clear, or query an option (given in the ‘key’ argument) in the back-end optimizer. Valid option keys are listed below.

Use value = NULL to remove an existing option. Leaving value blank will return the current value of the option specified by ‘key’.

To reset all options to their default values, use ‘reset = TRUE’. When reset = TRUE, ‘key’ and ‘value’ are ignored.

If the ‘model’ argument is set to NULL, the default optimizer option (i.e those applying to all models by default) will be set.

To see the defaults, use `getOption('mxOptions')`.

Before the model is submitted to the back-end, all keys and values are converted into strings using the [as.character](#) function.

The “Default optimizer” option can only be set globally (i.e., with model=NULL), and not locally (i.e., specifically to a given MxModel). Although the checkpointing options may be set globally, OpenMx’s behavior is only affected by locally set checkpointing options (that is, global checkpointing options are ignored at [runtime](#)).

Options “Gradient step size”, “Gradient iterations”, and “Function precision” have on-load global defaults of “Auto”. If value “Auto” is in effect for any of these three options at runtime, then OpenMx selects a reasonable numerical value in its place. These automated numerical values are intended to (1) adjust for the limited precision of the algorithm for computing multivariate-normal probability integrals, and (2) calculate accurate numeric derivatives at the optimizer’s solution. If the user replaces “Auto” with a valid numerical value, then OpenMx uses that value as-is.

Some options only affect certain optimizers. Option “Analytic Gradients” affects all three optimizers. Option “Gradient algorithm” is used by CSOLNP and SLSQP, and ignored by NPSOL. Option “Gradient iterations” only affects SLSQP. Option “Gradient step size” is used slightly differently by SLSQP and CSOLNP, and is ignored by NPSOL (see `mxComputeGradientDescent()` for details). If the MxModel contains `MxConstraints`, OpenMx’s interface to NPSOL scales “Feasibility tolerance” by multiplying it by 0.02 and dividing it by 0.05 before passing it to NPSOL; if there are no `MxConstraints`, OpenMx passes NPSOL a hardcoded value of 1e-5. Note that NPSOL’s criterion for returning a status code of 0 versus 1 for a given solution depends partly on “Optimality tolerance”.

For a block of  $n$  ordinal variables, the maximum number of integration points that OpenMx may use to calculate multivariate-normal probability integrals is given by  $mvnMaxPointsA + mvnMaxPointsB * n + mvnMaxPointsC * \exp(mvnMaxPointsD + mvnMaxPointsE * n * \log(mvnRelEps))$ . Integral approximation is stopped once either ‘mvnAbsEps’ or ‘mvnRelEps’ is satisfied. Use of ‘mvnAbsEps’ is deprecated.

The maximum number of major iterations (the option “Major iterations”) for optimization for NPSOL can be specified either by using a numeric value (such as 50, 1000, etc) or by specifying a user-defined function. The user-defined function should accept two arguments as input, the number of parameters and the number of constraints, and return a numeric value as output.

OpenMx options

Calculate Hessian	[Yes   No]	calculate the Hessian explicitly after optimization.
Standard Errors	[Yes   No]	return standard error estimates from the explicitly calculate hessian.
Default optimizer	[NPSOL   SLSQP   CSOLNP]	the gradient-descent optimizer to use
Number of Threads	[0 1 2 ... 10 ...]	number of threads used for optimization. Default value is taken from
Feasibility tolerance	$r$	the maximum acceptable absolute violations in linear and nonlinear c
Optimality tolerance	$r$	the accuracy with which the final iterate approximates a solution to th
Gradient algorithm	see list	finite difference method, either ‘forward’ or ‘central’.
Gradient iterations	1:4	the number of Richardson extrapolation iterations
Gradient step size	$r$	amount of change made to free parameters when numerically calculat
Analytic Gradients	[Yes   No]	should the optimizer use analytic gradients (if available)?
loglikelihoodScale	$i$	factor by which the loglikelihood is scaled.
Parallel diagnostics	[Yes   No]	whether to issue diagnostic messages about use of multiple threads
Nudge zero starts	[TRUE   FALSE]	Should OpenMx “nudge” starting values of zero to 0.1 at runtime?
Status OK	character vector	Status codes that are considered to indicate a successful optimization
Max minutes	numeric	Maximum backend elapsed time, in minutes

NPSOL-specific options

Nolist		this option suppresses printing of the options
Print level	$i$	the value of $i$ controls the amount of printout produced by the major iterations
Minor print level	$i$	the value of $i$ controls the amount of printout produced by the minor iterations
Print file	$i$	for $i > 0$ a full log is sent to the file with logical unit number $i$ .

Summary file	<i>i</i>	for $i > 0$ a brief log will be output to file <i>i</i> .
Function precision	<i>r</i>	a measure of accuracy with which the fitfunction and constraint functions can be computed.
Infinite bound size	<i>r</i>	if $r > 0$ defines the "infinite" bound bigbnd.
Major iterations	<i>i</i> or a function	the maximum number of major iterations before termination.
Verify level	[-1:3   Yes   No]	see NPSOL manual.
Line search tolerance	<i>r</i>	controls the accuracy with which a step is taken.
Derivative level	[0-3]	see NPSOL manual.
Hessian	[Yes   No]	return the Hessian (Yes) or the transformed Hessian (No).
Step Limit	<i>r</i>	maximum change in free parameters at first step of linesearch.

#### Checkpointing options

Always Checkpoint	[Yes   No]	whether to checkpoint all models during optimization.
Checkpoint Directory	path	the directory into which checkpoint files are written.
Checkpoint Prefix	string	the string prefix to add to all checkpoint filenames.
Checkpoint Fullpath	path	overrides the directory and prefix (useful to output to /dev/fd/2)
Checkpoint Units	see list	the type of units for checkpointing: 'minutes', 'iterations', or 'evaluations'.
Checkpoint Count	<i>i</i>	the number of units between checkpoint intervals.

#### Model transformation options

Error Checking	[Yes   No]	whether model consistency checks are performed in the OpenMx front-end
No Sort Data		character vector of model names for which FIML data sorting is not performed
RAM Inverse Optimization	[Yes   No]	whether to enable solve(I - A) optimization
RAM Max Depth	<i>i</i>	the maximum depth to be used when solve(I - A) optimization is enabled

#### Multivariate normal integration parameters

maxOrdinalPerBlock	<i>i</i>	maximum number of ordinal variables to evaluate together
mvnMaxPointsA	<i>i</i>	base number of integration points
mvnMaxPointsB	<i>i</i>	number of integration points per ordinal variable
mvnMaxPointsC	<i>i</i>	number of integration points per squared ordinal variables
mvnMaxPointsD	<i>i</i>	see details
mvnMaxPointsE	<i>i</i>	see details
mvnAbsEps	<i>i</i>	absolute error tolerance
mvnRelEps	<i>i</i>	relative error tolerance

#### Value

If a model is provided, it is returned with the optimizer option either set or cleared. If value is empty, the current value is returned.



**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

See [mxModel\(\)](#), as almost all uses of [mxOption\(\)](#) are via an [mxModel](#) whose options are set or cleared. See [mxComputeGradientDescent\(\)](#) for details on how different optimizers are affected by different options. See [as.statusCode](#) for information about the Status OK option.

**Examples**

```
# set the Numbder of Threads (cores to use)
mxOption(NULL, "Number of Threads", parallel::detectCores() - 1)

testModel <- mxModel(model = "testModel") # make a model to use for example
testModel$options # show the model options (none yet)
options()$mxOptions # list all mxOptions (global settings)

testModel <- mxOption(testModel, "Function precision", 1e-5) # set precision
testModel <- mxOption(testModel, "Function precision", NULL) # clear precision
# N.B. This is model-specific precision (defaults to global setting)

# may optimize for speed
# at cost of not getting standard errors
testModel <- mxOption(testModel, "Calculate Hessian", "No")
testModel <- mxOption(testModel, "Standard Errors" , "No")

testModel$options # see the list of options you set
```

---

MxOptionalChar-class *An optional character*

---

**Description**

An optional character

---

MxOptionalCharOrNumber-class  
*A character, integer, or NULL*

---

**Description**

A character, integer, or NULL

---

MxOptionalLogical-class

*An optional logical*

---

### Description

This is an internal class, the union of NULL and logical.

---

MxOptionalMatrix-class

*An optional matrix*

---

### Description

An optional matrix

---

MxOptionalNumeric-class

*An optional numeric*

---

### Description

An optional numeric

---

mxParametricBootstrap *Assess whether potential parameters should be freed using parametric bootstrap*

---

### Description

Data is simulated from 'nullModel'. The parameters named by 'labels' are freed to obtain the alternative model. The alternative model is fit against each simulated data set.

### Usage

```
mxParametricBootstrap(nullModel, labels,
  alternative=c("two.sided", "greater", "less"),
  ..., alpha=0.05, correction=p.adjust.methods,
  previousRun=NULL, replications=400, checkHess=FALSE,
  signif.stars = getOption("show.signif.stars"))
```

**Arguments**

nullModel	The model specifying the null distribution
labels	A character vector of parameters to free to obtain the alternative model
alternative	a character string specifying the alternative hypothesis
...	Not used. Forces remaining arguments to be specified by name.
alpha	The false positive rate
correction	How to adjust the p values for multiple tests.
replications	The number of resampling replications. If available, replications from prior invocation will be reused.
previousRun	Results to re-use from a previous bootstrap.
checkHess	Whether to approximate the Hessian in each replication
signif.stars	logical. If TRUE, 'significance stars' are printed for each coefficient.

**Details**

When the model has a default compute plan and 'checkHess' is kept at FALSE then the Hessian will not be approximated or checked. On the other hand, 'checkHess' is TRUE then the Hessian will be approximated by finite differences. This procedure is of some value because it can be informative to check whether the Hessian is positive definite (see [mxComputeHessianQuality](#)). However, approximating the Hessian is often costly in terms of CPU time. For bootstrapping, the parameter estimates derived from the resampled data are typically of primary interest.

**Value**

A data frame is returned containing the test results. Details of the bootstrap replications are stored in the 'bootData' attribute on the data frame.

**Examples**

```
library(OpenMx)

data(demoOneFactor)
manifests <- names(demoOneFactor)
latents <- c("G")

base <- mxModel(
  "OneFactorCov", type="RAM",
  manifestVars = manifests,
  latentVars = latents,
  mxPath(from=latents, to=manifests, values=0, free=FALSE, labels=paste0('l',1:length(manifests))),
  mxPath(from=manifests, arrows=2, values=rlnorm(length(manifests)), lbound=.01),
  mxPath(from=latents, arrows=2, free=FALSE, values=1.0),
  mxPath(from = 'one', to = manifests, values=0, free=TRUE, labels=paste0('m',1:length(manifests))),
  mxData(demoOneFactor, type="raw")

base <- mxRun(base)
```

```
# use more replications, 8 is for demonstration purpose only
mxParametricBootstrap(base, paste0('1', 1:length(manifests)),
  "two.sided", replications=8)
```

mxPath

*Create List of Paths***Description**

This function creates a list of paths.

**Usage**

```
mxPath(from, to = NA, connect = c("single", "all.pairs", "unique.pairs",
  "all.bivariate", "unique.bivariate"), arrows = 1,
  free = TRUE, values = NA, labels = NA,
  lbound = NA, ubound = NA, ..., joinKey = as.character(NA))
```

**Arguments**

from	character vector. These are the sources of the new paths.
to	character vector. These are the sinks of the new paths.
connect	String. Specifies the type of source to sink connection: "single", "all.pairs", "all.bivariate", "unique.pairs", "unique.bivariate". Default value is "single".
arrows	numeric value. Must be either 1 (for single-headed) or 2 (for double-headed arrows).
free	boolean vector. Indicates whether paths are free or fixed.
values	numeric vector. The starting values of the parameters.
labels	character vector. The names of the paths.
lbound	numeric vector. The lower bounds of free parameters.
ubound	numeric vector. The upper bounds of free parameters.
...	Not used. Allows OpenMx to catch the use of the deprecated 'all' argument.
joinKey	character vector. The name of the foreign key to join against some other model to create a cross model path (regression or factor loading).

**Details**

The mxPath function creates [MxPath](#) objects. These consist of a list of paths describing the relationships between variables in a model using the RAM modeling approach (McArdle and MacDonald, 1984). Variables are referenced by name, and these names must appear in the 'manifestVar' and 'latentVar' arguments of the [mxModel](#) function.

Paths are specified as going "from" one variable (or set of variables) "to" another variable or set of variables using the 'from' and 'to' arguments, respectively. If 'to' is left empty, it will be set to the value of 'from'.

'connect' has five possible connection types: "single", "all.pairs", "all.bivariate", "unique.pairs", "unique.bivariate". The default value is "single". Assuming the values c('a','b','c') for the 'to' and 'from' fields the paths produced by each connection type are as follows:

**"all.pairs"**: (a,a), (a,b), (a,c), (b,a), (b,b), (b,c), (c,a), (c,b), (c,c).

**"unique.pairs"**: (a,a), (a,b), (a,c), (b,b), (b,c), (c,c).

**"all.bivariate"**: (a,b), (a,c), (b,a), (b,c), (c,a), (c,b).

**"unique.bivariate"**: (a,b), (a,c), (b,c).

**"single"**: (a,a), (b,b), (c,c).

Multiple variables may be input as a vector of variable names. If the 'connect' argument is set to "single", then paths are created going from each entry in the 'from' vector to the corresponding entry in the 'to' vector. If the 'to' and 'from' vectors are of different lengths when the 'connect' argument is set to "single", the shorter vector is repeated to make the vectors of equal length.

The 'free' argument specifies whether the paths created by the mxPath function are free or fixed parameters. This argument may take either TRUE for free parameters, FALSE for fixed parameters, or a vector of TRUEs and FALSEs to be applied in order to the created paths.

The 'arrows' argument specifies the type of paths created. A value of 1 indicates a one-headed arrow representing regression. This path represents a regression of the 'to' variable on the 'from' variable, such that the arrow points to the 'to' variable in a path diagram. A value of 2 indicates a two-headed arrow, representing a covariance or variance. If multiple paths are created in the same mxPath function, then the 'arrows' argument may take a vector of 1s and 2s to be applied to the set of created paths.

The 'values' is a numeric vectors containing the starting values of the created paths. 'values' gives a starting value for estimation. The 'labels' argument specifies the names of the resulting **MxPath** object. The 'lbound' and 'ubound' arguments specify lower and upper bounds for the created paths.

### Value

Returns a list of paths.

### Note

The previous implementation of 'all' had unsafe features. Its use is now deprecated, and has been replaced by the new mechanism 'connect' which supports safe and controlled generation of desired combinations of paths.

### References

McArdle, J. J. and MacDonald, R. P. (1984). Some algebraic properties of the Reticular Action Model for moment structures. *British Journal of Mathematical and Statistical Psychology*, 37, 234-251.

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

### See Also

[mxMatrix](#) for a matrix-based approach to path specification; [mxModel](#) for the container in which mxPaths are embedded. More information about the OpenMx package may be found [here](#).

## Examples

```

# A simple Example: 1 factor Confirmatory Factor Analysis

library(OpenMx)

data(demoOneFactor)
manifests <- names(demoOneFactor)
latents  <- c("G")
factorModel <- mxModel(model="One Factor", type="RAM",
  manifestVars = manifests,
  latentVars  = latents,
  mxPath(from=latents, to=manifests),
  mxPath(from=manifests, arrows=2),
  mxPath(from=latents, arrows=2, free=FALSE, values=1.0),
  mxData(cov(demoOneFactor), type="cov", numObs=500)
)
factorFit <- mxRun(factorModel)
summary(factorFit)

# A more complex example using features of R to compress
# what would otherwise be a long and error-prone script

# list of 100 variable names: "01" "02" "03"...
myManifest <- sprintf("%02d", c(1:100))

# the latent variables for the model
myLatent <- c("G1", "G2", "G3", "G4", "G5")

# Start building the model:
# Define its type, and add the manifest and latent variable name lists
testModel <- mxModel(model="testModel", type = "RAM",
  manifestVars = myManifest, latentVars = myLatent)

# Create covariances between the latent variables and add to the model
# Here we use combn to create the covariances
# nb: To create the variances and covariances in one operation you could use
# expand.grid(myLatent,myLatent) to specify from and to

uniquePairs <- combn(myLatent,2)
covariances <- mxPath(from = uniquePairs[1,],
  to=uniquePairs[2,], arrows = 2, free = TRUE, values = 1)
testModel <- mxModel(model=testModel, covariances)

# Create variances for the latent variables
variances <- mxPath(from = myLatent,
  to=myLatent, arrows = 2, free = TRUE, values = 1)
testModel <- mxModel(model=testModel, variances) # add variances to the model

# Make a list of paths from each packet of 20 manifests
# to one of the 5 latent variables
# nb: The first loading to each latent is fixed to 1 to scale its variance.

```

```

singles <- list()
for (i in 1:5) {
  j <- i*20
  singles <- append(singles, mxPath(
    from = myLatent[i], to = myManifest[(j - 19):j],
    arrows = 1,
    free = c(FALSE, rep(TRUE, 19)),
    values = c(1, rep(0.75, 19)))
}

# add single-headed paths to the model
testModel <- mxModel(model=testModel, singles)

```

---

mxPearsonSelCov	<i>Perform Pearson Aitken selection</i>
-----------------	---

---

## Description

These functions implement the Pearson Aitken selection formulae.

## Usage

```

mxPearsonSelCov(origCov, newCov)
mxPearsonSelMean(origCov, newCov, origMean)

```

## Arguments

origCov	covariance matrix. The covariance prior to selection.
newCov	covariance matrix. A subset of origCov to replace.
origMean	column vector. A mean vector to adjust.

## Details

Both mxPearsonSelCov and mxPearsonSelMean match the dimnames of newCov and origCov to determine which partition of origCov to replace with newCov.

Let the  $n \times n$  covariance matrix  $R$  (origCov) be partitioned into non-empty, disjoint sets  $p$  and  $q$ . Let  $R_{ij}$  denote the covariance matrix between the  $p$  and  $q$  variables where the subscripts denote the variable subsets (e.g.  $R_{pq}$ ). Let column vectors  $\mu_p$  and  $\mu_q$  contain the means of  $p$  and  $q$  variables, respectively. We wish to compute the conditional covariances of the variables in  $q$  for a subset of the population where  $R_{pp}$  and  $\mu_p$  are known (or partially known)—that is, we wish to *condition* the covariances and means of  $q$  on those of  $p$ . Let  $V_{pp}$  (newCov) be an arbitrary covariance matrix of the same dimension as  $R_{pp}$ . If we replace  $R_{pp}$  by  $V_{pp}$  then the mean of  $q$  (origMean) is transformed as

$$\mu_q \rightarrow \mu_q + R_{qp}R_{pp}^{-1}\mu_p$$

and the covariance of  $p$  and  $q$  are transformed as

$$\left[ \begin{array}{c|c} R_{pp} & R_{pq} \\ \hline R_{qp} & R_{qq} \end{array} \right] \rightarrow \left[ \begin{array}{c|c} V_{pp} & V_{pp}R_{pp}^{-1}R_{pq} \\ \hline R_{qp}R_{pp}^{-1}V_{pp} & R_{qq} - R_{qp}(R_{pp}^{-1} - R_{pp}^{-1}V_{pp}R_{pp}^{-1})R_{pq} \end{array} \right]$$

## References

Aitken, A. (1935). Note on selection from a multivariate normal population. *Proceedings of the Edinburgh Mathematical Society (Series 2)*, 4(2), 106-110. doi:10.1017/S0013091500008063

## Examples

```
library(OpenMx)

m1 <- mxModel(
  'selectionTest',
  mxMatrix('Full', 10, 10, values=rWishart(1, 20, toeplitz((10:1)/10))[, ,1],
    dimnames=list(paste0('c',1:10),paste0('c',1:10)), name="m1"),
  mxMatrix('Full', 2, 2, values=diag(2),
    dimnames=list(paste0('c',1:2),paste0('c',1:2)), name="m2"),
  mxMatrix('Full', 10, 1, values=runif(10),
    dimnames=list(paste0('c',1:10),c('v')), name="u1"),
  mxAlgebra(mxPearsonSelCov(m1, m2), name="c1"),
  mxAlgebra(mxPearsonSelMean(m1, m2, u1), name="u2")
)

m1 <- mxRun(m1)
```

---

 mxPowerSearch

*Power curve*


---

## Description

Determine the power curve between true and false models

## Usage

```
mxPowerSearch(trueModel, falseModel, n=NULL, sig.level=0.05, ...,
  probes=300L, previousRun=NULL,
  gdFun=mxGenerateData,
  method=c('empirical', 'ncp'),
  grid=NULL,
  statistic=c('LRT', 'AIC', 'BIC'),
  OK=mxOption(trueModel, "Status OK"),
  checkHess=FALSE,
  silent=!interactive())

mxPower(trueModel, falseModel, n=NULL, sig.level=0.05, power=0.8, ...,
  probes=300L, gdFun=mxGenerateData,
  method=c('empirical', 'ncp'),
  statistic=c('LRT', 'AIC', 'BIC'),
  OK=mxOption(trueModel, "Status OK"), checkHess=FALSE,
  silent=!interactive())
```



**Arguments**

trueModel	The true generating model for the data.
falseModel	The model representing the null hypothesis that we wish to reject.
n	Average group sample size. When NULL, finds the relationship between sample size and power. When given, finds the relationship between a parameter and power (at the given sample size).
sig.level	The false positive rate (a.k.a. type 1 error).
power	The power (a.k.a. 1 - type 2 error).
...	Not used.
probes	The number of probes to use when method='empirical'.
previousRun	Output from a prior run of 'mxPowerSearch' to extend.
gdFun	The function invoked to generate new data for each Monte Carlo probe.
method	To estimate power using the Monte Carlo method ('empirical') or the average non-centrality method ('ncp').
grid	A vector of locations at which to evaluate the power. If not provided, a reasonable default will be chosen.
statistic	Which test to use to compare models.
OK	The set of status code that are considered successful
checkHess	Whether to approximate the Hessian in each replication
silent	Whether to output a progress indicator.

**Details**

Power is the chance of obtaining a significant difference when there is a significant difference (1 - false negative rate). The likelihood ratio test is used by default. There are two methods available to produce a power curve. The default, `method=empirical`, works for any model where the likelihood ratio test works. For example, definition variables and missing data are fine, but parameters estimated at upper or lower bounds will cause problems. The `method=empirical` can require a lot of time because the models need to be fit 100s of times. An alternate approach, `method=ncp`, is much more efficient and takes advantage of the fact that the non-null distribution of likelihood ratio test statistic is often  $\chi^2(df_1 - df_0, N\lambda)$ ,  $chi^2(df_1 - df_0, Nlambda)$ . That is, the non-centrality parameter,  $\lambda$ , *lambda*, can be assumed, on average, to contribute equally per row. This permits essentially instant power curves without the burden of tedious simulation. However, definition variables, missing data, or unconventional models (e.g., mixture distributions) can violate this assumption. Therefore, we recommend verifying that the output from `method=empirical` roughly matches `method=ncp` on the model of interest before relying on `method=ncp`. Unlike `method=empirical`, `method=ncp` does not use the `gdFun` argument and works with models that only have summary statistics for data.

When `method=ncp`, parameters of both 'trueModel' and 'falseModel' are assumed to be converged to their desired values. In contrast, when `method=empirical`, 'trueModel' need not be run or even contain data. On each replication, data are generated from 'trueModel' at the given parameter vector. Both 'trueModel' and 'falseModel' are fit against these data.

When `statistic='LRT'` then the models must be nested and `sig.level` is used to determine whether the test is rejected. For 'AIC' and 'BIC', the test is regarded as rejected when the 'trueModel' obtains a lower score than the 'falseModel'. In contrast to `statistic='LRT'`, there is no nesting requirement. For example, 'AIC' can be used to compare a 'trueModel' against its corresponding saturated model.

`mxPower` operates in many modes. When power is passed as NULL then power is calculated and returned. When power (as a scalar or vector) is given then sample or effect size is (are) returned. If you pass a list of models for 'falseModel', each model will be checked in turn and the results returned as a vector. If you pass a vector of sample sizes, each sample size will be checked in turn and the results returns as a vector.

In contrast to `mxPower`, `mxPowerSearch` attempts to model the whole relationship between sample size or effect size and power. A naive Monte Carlo estimate of power examines a single candidate sample size at a time. To obtain the whole curve, and simultaneously, to reduce the number of simulation probes, `mxPowerSearch` employs a binomial family generalized linear model with a logit link to predict the power curve across the sample sizes of interest (similar to Schoemann et al, 2014).

The `mxPowerSearch` algorithm works in 3 stages. Without loss of generality, our description will assume a sample size to power relationship, but a similar process is used for the parameter value to power relationship. In the first stage, a crude binary search is used to find the range reasonable values for N. This stage is complete once we have at least two rejections and at least two non-rejections. At this point, the binomial intercept and slope model is fit to these data. If the  $p$ -value for the slope is less than 0.25 then we jump to stage 3. Otherwise, we fit an intercept only binomial model. Our goal is to nail down the intercept (where power=0.5) because this is the easiest point to find and is a necessary prerequisite to estimate the variance (a.k.a. slope). Therefore, we probe at the median of previous probes stepping by 10% in the direction of the model's predicted intercept. Eventually, after enough probes, we reach stage 3 where the  $p$ -value for the slope is less than 0.25. At stage 3, our goal is to nail down the interesting part of the power curve. Therefore, we cycle serially through probes at 0, 1, and 2 logits from the intercept. This process is continued for the permitted number of probes. Occasionally, the  $p$ -value for the slope in the stage 3 model grows larger than 0.25. In this case, we switch back to stage 2 (intercept only) until the stage 3 model start working again. There is no other convergence criteria. Accuracy continues to improves until the probe limit is reached. After `mxPowerSearch` returns, additional probes can be run by passing the previous result back into the function as the `previousRun` argument.

When 'n' is fixed then `mxPowerSearch` helps answer the question, "how small of a true effect is likely to be detected at a particular sample size?" Only one parameter can be considered at a time. The way the simulation works is that a candidate value for the parameter of interest is loaded into the `trueModel`, data are generated, then both the true and false model are fit to the data to obtain the difference in fit. The candidate parameter is initially set to halfway between the `trueModel` and `falseModel`. The power curve will reflect the smallest distance, relative to the false model, required to have a good chance to reject the false model according to the chosen statistic.

Note that the default grid is chosen to exhibit the interesting part of the power curve (from 0.25 to 0.97). Especially for `method=ncp`, this curve is practically identical for any pair of models (but located at a different range of sample sizes). You should select your own `grid` points if you wish to align power curves from more than one power analysis.

**Value**

mxPower returns a vector of sample sizes, powers, or effect sizes.

mxPowerSearch returns a data.frame with one row for each 'grid' point. The first column is either the sample size 'N' or the parameter label. The second column is the power. The next two columns provide a +/-2 SE confidence interval for the power as estimated by the binomial logit linear model. When method=empirical then the 'probes' attribute contains a data.frame record of the activity of the power estimation process.

**References**

Schoemann, A. M., Miller, P., Pornprasertmanit, S. & Wu, W. (2014). Using Monte Carlo simulations to determine power and sample size for planned missing designs. *International Journal of Behavioral Development*, 38(5), 471-479.

**See Also**

[mxCompare](#), [mxRefModels](#)

**Examples**

```
library(OpenMx)

data(demoOneFactor)
manifests <- names(demoOneFactor)
latents <- c("G")
factorModel <- mxModel("One Factor",
                        type="RAM",
                        manifestVars = manifests,
                        latentVars = latents,
                        mxPath(from=latents, to=manifests, values=0.8),
                        mxPath(from=manifests, arrows=2, values=1),
                        mxPath(from=latents, arrows=2,
                                free=FALSE, values=1.0),
                        mxPath(from="one", to=manifests),
                        mxData(demoOneFactor, type="raw"))
factorModelFit <- mxRun(factorModel)

indModel <- factorModelFit
indModel$A$values['x1', 'G'] <- 0.3
indModel$A$free['x1', 'G'] <- FALSE
indModel <- mxRun(indModel)

# What power do we have at different sample sizes
# to detect that the G to x1 factor loading is
# really 0.3 instead of 0.39?
mxPowerSearch(factorModelFit, indModel, method='ncp')

# If we want to conduct a study with 80% power to
# find that the G to x1 factor loading is
# really 0.3 instead of 0.39, what sample size
# should we use?
```

```
mxPower(factorModelFit, indModel, method='ncp')
```

---

MxRAMGraph-class	<i>MxRAMGraph</i>
------------------	-------------------

---

### Description

This is an internal class and should not be used directly. It is a class for RAM directed graphs.

---

MxRAMMetaData-class	<i>Meta Data for RAM</i>
---------------------	--------------------------

---

### Description

This is an internal class, the meta data for RAM.

---

MxRAMModel-class	<i>MxRAMModel</i>
------------------	-------------------

---

### Description

This is an internal class and should not be used directly.

---

mxRAMObjective	<i>DEPRECATED: Create MxRAMObjective Object</i>
----------------	---

---

### Description

WARNING: Objective functions have been deprecated as of OpenMx 2.0.

Please use `mxExpectationRAM()` and `mxFitFunctionML()` instead. As a temporary workaround, `mxRAMObjective` returns a list containing an `MxExpectationNormal` object and an `MxFitFunctionML` object.

All occurrences of

`mxRAMObjective(A, S, F, M = NA, dimnames = NA, thresholds = NA, vector = FALSE, threshnames = dimnames)`

Should be changed to

`mxExpectationRAM(A, S, F, M = NA, dimnames = NA, thresholds = NA, threshnames = dimnames) mxFitFunctionML(vector = FALSE)`

**Arguments**

A	A character string indicating the name of the 'A' matrix.
S	A character string indicating the name of the 'S' matrix.
F	A character string indicating the name of the 'F' matrix.
M	An optional character string indicating the name of the 'M' matrix.
dimnames	An optional character vector to be assigned to the column names of the 'F' and 'M' matrices.
thresholds	An optional character string indicating the name of the thresholds matrix.
vector	A logical value indicating whether the objective function result is the likelihood vector.
threshnames	An optional character vector to be assigned to the column names of the thresholds matrix.

**Details**

NOTE: THIS DESCRIPTION IS DEPRECATED. Please change to using [mxExpectationRAM](#) and [mxFitFunctionML](#) as shown in the example below.

Objective functions were functions for which free parameter values are chosen such that the value of the objective function was minimized. The `mxRAMObjective` provided maximum likelihood estimates of free parameters in a model of the covariance of a given [MxData](#) object. This model is defined by reticular action modeling (McArdle and McDonald, 1984). The 'A', 'S', and 'F' arguments must refer to [MxMatrix](#) objects with the associated properties of the A, S, and F matrices in the RAM modeling approach.

The 'dimnames' argument takes an optional character vector. If this argument is not a single NA, then this vector be assigned to be the column names of the 'F' matrix and optionally to the 'M' matrix, if the 'M' matrix exists.

The 'A' argument refers to the A or asymmetric matrix in the RAM approach. This matrix consists of all of the asymmetric paths (one-headed arrows) in the model. A free parameter in any row and column describes a regression of the variable represented by that row regressed on the variable represented in that column.

The 'S' argument refers to the S or symmetric matrix in the RAM approach, and as such must be square. This matrix consists of all of the symmetric paths (two-headed arrows) in the model. A free parameter in any row and column describes a covariance between the variable represented by that row and the variable represented by that column. Variances are covariances between any variable at itself, which occur on the diagonal of the specified matrix.

The 'F' argument refers to the F or filter matrix in the RAM approach. If no latent variables are included in the model (i.e., the A and S matrices are of both of the same dimension as the data matrix), then the 'F' should refer to an identity matrix. If latent variables are included (i.e., the A and S matrices are not of the same dimension as the data matrix), then the 'F' argument should consist of a horizontal adhesion of an identity matrix and a matrix of zeros.

The 'M' argument refers to the M or means matrix in the RAM approach. It is a 1 x n matrix, where n is the number of manifest variables + the number of latent variables. The M matrix must be specified if either the `mxData` type is "cov" or "cor" and a means vector is provided, or if the `mxData` type is "raw". Otherwise the M matrix is ignored.

The `MxMatrix` objects included as arguments may be of any type, but should have the properties described above. The `mxRAMObjective` will not return an error for incorrect specification, but incorrect specification will likely lead to estimation problems or errors in the `mxRun` function.

`mxRAMObjective` evaluates with respect to an `MxData` object. The `MxData` object need not be referenced in the `mxRAMObjective` function, but must be included in the `MxModel` object. `mxRAMObjective` requires that the 'type' argument in the associated `MxData` object be equal to 'cov' or 'cor'.

To evaluate, place `MxRAMObjective` objects, the `mxData` object for which the expected covariance approximates, referenced `MxAlgebra` and `MxMatrix` objects, and optional `MxBounds` and `MxConstraint` objects in an `MxModel` object. This model may then be evaluated using the `mxRun` function. The results of the optimization can be found in the 'output' slot of the resulting model, and may be obtained using the `mxEval` function..

### Value

Returns a list containing an `MxExpectationRAM` object and an `MxFitFunctionML` object.

### References

McArdle, J. J. and MacDonald, R. P. (1984). Some algebraic properties of the Reticular Action Model for moment structures. *British Journal of Mathematical and Statistical Psychology*, 37, 234-251.

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

### Examples

```
# Create and fit a model using mxMatrix, mxAlgebra,
# mxExpectationNormal, and mxFitFunctionML

library(OpenMx)

# Simulate some data

x=rnorm(1000, mean=0, sd=1)
y= 0.5*x + rnorm(1000, mean=0, sd=1)
tmpFrame <- data.frame(x, y)
tmpNames <- names(tmpFrame)

# Define the matrices

matrixS <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(1,0,0,1),
                    free=c(TRUE,FALSE,FALSE,TRUE), labels=c("Vx", NA, NA, "Vy"),
                    name = "S")
matrixA <- mxMatrix(type = "Full", nrow = 2, ncol = 2, values=c(0,1,0,0),
                    free=c(FALSE,TRUE,FALSE,FALSE), labels=c(NA, "b", NA, NA),
                    name = "A")
matrixF <- mxMatrix(type="Iden", nrow=2, ncol=2, name="F")
matrixM <- mxMatrix(type = "Full", nrow = 1, ncol = 2, values=c(0,0),
```

```

        free=c(TRUE,TRUE), labels=c("Mx", "My"), name = "M")

# Define the expectation

expFunction <- mxExpectationRAM(M="M", dimnames = tmpNames)

# Choose a fit function

fitFunction <- mxFitFunctionML()

# Define the model

tmpModel <- mxModel(model="exampleRAMModel",
                    matrixA, matrixS, matrixF, matrixM,
                    expFunction, fitFunction,
                    mxData(observed=cov(tmpFrame), type="cov", numObs=nrow(tmpFrame),
                             means = colMeans(tmpFrame)))

# Fit the model and print a summary

tmpModelOut <- mxRun(tmpModel)
summary(tmpModelOut)

```

---

mxRename

*Rename MxModel or a Submodel*


---

## Description

This functions renames either the top model or a submodel to a new name. All internal references to the old model name are replaced with references to the new name.

## Usage

```
mxRename(model, newname, oldname = NA)
```

## Arguments

model	a MxModel object.
newname	the new name of the model.
oldname	the name of the target model to rename. If NA then rename top model.

## Value

Return a `mxModel` object with the target model renamed.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## Examples

```
library(OpenMx)

# create two empty models
modelA <- mxModel(model='modelA')
modelB <- mxModel(model='modelB')

# create a parent model with two submodels
modelC <- mxModel(model='modelC', modelA, modelB)

# Rename modelC to model1
model1 <- mxRename(modelC, 'model1')

# Rename submodel modelB to model2
model1 <- mxRename(model1, oldname = 'modelB', newname = 'model2')

model1
```

---

 mxRestore

*Restore From Checkpoint File*


---

## Description

The function loads the last saved state from a checkpoint file.

## Usage

```
mxRestore(model, chkpt.directory = ".", chkpt.prefix = "", line=NULL, strict=FALSE)
```

## Arguments

model	<a href="#">MxModel</a> object to be loaded.
chkpt.directory	character. Directory where the checkpoint file is located.
chkpt.prefix	character. Prefix of the checkpoint file.
line	integer. Which line from the checkpoint file to restore (defaults to the last line)
strict	logical. Require that the checkpoint name and model name match.

## Details

In general, the arguments ‘chkpt.directory’ and ‘chkpt.prefix’ should be identical to the [mxOption](#): ‘Checkpoint Directory’ and ‘Checkpoint Prefix’ that were specified on the model before execution.

Alternatively, the checkpoint file can be manually loaded as a data.frame in R. Use [read.table](#) with the options header=TRUE, sep="\t", stringsAsFactors=FALSE, check.names=FALSE.



**Value**

Returns an MxModel object with free parameters updated to the last saved values. When 'line' is provided, the MxModel is updated to the values on that line within the checkpoint file.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
library(OpenMx)

# Simulate some data

x=rnorm(1000, mean=0, sd=1)
y= 0.5*x + rnorm(1000, mean=0, sd=1)
tmpFrame <- data.frame(x, y)
tmpNames <- names(tmpFrame)

# Create a model that includes an expected covariance matrix,
# an expectation function, a fit function, and an observed covariance matrix

data <- mxData(cov(tmpFrame), type="cov", numObs = 1000)
expCov <- mxMatrix(type="Symm", nrow=2, ncol=2, values=c(.2,.1,.2), free=TRUE, name="expCov")
expFunction <- mxExpectationNormal(covariance="expCov", dimnames=tmpNames)
fitFunction <- mxFitFunctionML()
testModel <- mxModel(model="testModel", expCov, data, expFunction, fitFunction)

#Use mxRun to optimize the free parameters in the expected covariance matrix
modelOut <- mxRun(testModel, checkpoint = TRUE)
modelOut$expCov

#Use mxRestore to load the last checkpoint saved state of the model
modelRestore <- mxRestore(testModel)
modelRestore$expCov
```

---

mxRetro

*Return random classic Mx error message*


---

**Description**

This function allows you to obtain a classic Mx error message. The message returned is random.

**Usage**

```
mxRetro()
```

**Details**

If you're a nostalgic old sod and you miss the warm, fuzzy feelings you got from reading one of Mike Neale's patented error messages, then this function is here to save you from the depths of dire depression. All credit for this function is due to Sarah Medland, but of course the wisdom is from Mike Neale.

**References**

- <https://en.wikipedia.org/wiki/OpenMx>

**See Also**

- [omxBrownie](#)

**Examples**

```
require(OpenMx)
mxRetro()
```

---

mxROjective

*DEPRECATED: Create MxROjective Object*

---

**Description**

WARNING: Objective functions have been deprecated as of OpenMx 2.0.

Please use `mxFitFunctionR()` instead. As a temporary workaround, `mxROjective` returns a list containing a NULL `MxExpectation` object and an `MxFitFunctionR` object.

All occurrences of

`mxROjective(fitfun, ...)`

Should be changed to

`mxFitFunctionR(fitfun, ...)`

**Arguments**

`objfun`            A function that accepts two arguments.

`...`                The initial state information to the objective function.

**Details**

NOTE: THIS DESCRIPTION IS DEPRECATED. Please change to using [mxExpectationNormal](#) and [mxFitFunctionML](#) as shown in the example below.

The `fitfun` argument must be a function that accepts two arguments. The first argument is the `mxModel` that should be evaluated, and the second argument is some persistent state information that can be stored between one iteration of optimization to the next iteration. It is valid for the function to simply ignore the second argument.

The function must return either a single numeric value, or a list of exactly two elements. If the function returns a list, the first argument must be a single numeric value and the second element will be the new persistent state information to be passed into this function at the next iteration. The single numeric value will be used by the optimizer to perform optimization.

The initial default value for the persistent state information is NA.

Throwing an exception (via stop) from inside fitfun may result in unpredictable behavior. You may want to wrap your code in tryCatch while experimenting.

## Value

Returns a list containing a NULL mxExpectation object and an MxFitFunctionR object.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## Examples

```
# Create and fit a model using mxFitFunctionR

library(OpenMx)

A <- mxMatrix(nrow = 2, ncol = 2, values = c(1:4), free = TRUE, name = 'A')
squared <- function(x) { x ^ 2 }

# Define the objective function in R

objFunction <- function(model, state) {
  values <- model$A$values
  return(squared(values[1,1] - 4) + squared(values[1,2] - 3) +
         squared(values[2,1] - 2) + squared(values[2,2] - 1))
}

# Define the expectation function

fitFunction <- mxFitFunctionR(objFunction)

# Define the model

tmpModel <- mxModel(model="exampleModel", A, fitFunction)

# Fit the model and print a summary

tmpModelOut <- mxRun(tmpModel)
summary(tmpModelOut)
```

---

 mxRowObjective

 DEPRECATED: Create MxRowObjective Object
 

---

### Description

WARNING: Objective functions have been deprecated as of OpenMx 2.0.

Please use mxFitFunctionRow() instead. As a temporary workaround, mxRowObjective returns a list containing a NULL MxExpectation object and an MxFitFunctionRow object.

All occurrences of

```
mxRowObjective(rowAlgebra, reduceAlgebra, dimnames, rowResults = "rowResults", filteredDataRow = "filteredDataRow", existenceVector = "existenceVector")
```

Should be changed to

```
mxFitFunctionRow(rowAlgebra, reduceAlgebra, dimnames, rowResults = "rowResults", filteredDataRow = "filteredDataRow", existenceVector = "existenceVector")
```

### Arguments

rowAlgebra	A character string indicating the name of the algebra to be evaluated row-wise.
reduceAlgebra	A character string indicating the name of the algebra that collapses the row results into a single number which is then optimized.
dimnames	A character vector of names corresponding to columns be extracted from the data set.
rowResults	The name of the auto-generated "rowResults" matrix. See details.
filteredDataRow	The name of the auto-generated "filteredDataRow" matrix. See details.
existenceVector	The name of the auto-generated "existenceVector" matrix. See details.

### Details

Objective functions are functions for which free parameter values are chosen such that the value of the objective function is minimized. The mxRowObjective function evaluates a user-defined [MxAlgebra](#) object called the 'rowAlgebra' in a row-wise fashion. It then stores results of the row-wise evaluation in another [MxAlgebra](#) object called the 'rowResults'. Finally, the mxRowObjective function collapses the row results into a single number which is then used for optimization. The [MxAlgebra](#) object named by the 'reduceAlgebra' collapses the row results into a single number.

The 'filteredDataRow' is populated in a row-by-row fashion with all the non-missing data from the current row. You cannot assume that the length of the filteredDataRow matrix remains constant (unless you have no missing data). The 'existenceVector' is populated in a row-by-row fashion with a value of 1.0 in column j if a non-missing value is present in the data set in column j, and a value of 0.0 otherwise. Use the functions [omxSelectRows](#), [omxSelectCols](#), and [omxSelectRowsAndCols](#) to shrink other matrices so that their dimensions will be conformable to the size of 'filteredDataRow'.

**Value**

Please use `mxFitFunctionRow()` instead. As a temporary workaround, `mxRowObjective` returns a list containing a NULL `MxExpectation` object and an `MxFitFunctionRow` object.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
# Model that adds two data columns row-wise, then sums that column
# Notice no optimization is performed here.

library(OpenMx)

xdat <- data.frame(a=rnorm(10), b=1:10) # Make data set
amod <- mxModel(model="example1",
  mxData(observed=xdat, type='raw'),
  mxAlgebra(sum(filteredDataRow), name = 'rowAlgebra'),
  mxAlgebra(sum(rowResults), name = 'reduceAlgebra'),
  mxFitFunctionRow(
    rowAlgebra='rowAlgebra',
    reduceAlgebra='reduceAlgebra',
    dimnames=c('a','b'))
)
amodOut <- mxRun(amod)
mxEval(rowResults, model=amodOut)
mxEval(reduceAlgebra, model=amodOut)

# Model that find the parameter that minimizes the sum of the
# squared difference between the parameter and a data row.

bmod <- mxModel(model="example2",
  mxData(observed=xdat, type='raw'),
  mxMatrix(values=.75, ncol=1, nrow=1, free=TRUE, name='B'),
  mxAlgebra((filteredDataRow - B) ^ 2, name='rowAlgebra'),
  mxAlgebra(sum(rowResults), name='reduceAlgebra'),
  mxFitFunctionRow(
    rowAlgebra='rowAlgebra',
    reduceAlgebra='reduceAlgebra',
    dimnames=c('a'))
)
bmodOut <- mxRun(bmod)
mxEval(B, model=bmodOut)
mxEval(reduceAlgebra, model=bmodOut)
mxEval(rowResults, model=bmodOut)
```

mxRun

*Send a Model to the Optimizer***Description**

This function begins optimization, sending ‘model’ to the optimizer.

Optionally, confidence ‘intervals’ will also be computed.

During a run, ‘mxRun’ will print the context (e.g. optimizer name or step in the analysis e.g. MxComputeNumericDeriv ), followed by the current evaluation count, fit value, and the change in fit compared to the last status report. e.g.:

```
SLSQP 668 4966.58 -218.8
```

note: For models that prove difficult to run, you might look at [mxTryHard](#).

**Usage**

```
mxRun(model, ..., intervals = NULL, silent = FALSE, suppressWarnings = FALSE,
       unsafe = FALSE, checkpoint = FALSE, useSocket = FALSE, onlyFrontend = FALSE,
       useOptimizer = TRUE)
```

**Arguments**

model	A <a href="#">MxModel</a> object to be optimized.
...	Not used. Forces remaining arguments to be specified by name.
intervals	A boolean indicating whether to compute the specified confidence intervals.
silent	A boolean indicating whether to print status to terminal.
suppressWarnings	A boolean indicating whether to suppress warnings.
unsafe	A boolean indicating whether to ignore errors.
checkpoint	A boolean indicating whether to periodically write parameter values to a file.
useSocket	A boolean indicating whether to periodically write parameter values to a socket.
onlyFrontend	A boolean indicating whether to run only front-end model transformations.
useOptimizer	A boolean indicating whether to run only the log-likelihood of the current free parameter values but not move any of the free parameters.

**Details**

The mxRun function is used to optimize free parameters in [MxModel](#) objects based on an expectation function and fit function. MxModel objects included in the mxRun function must include an appropriate expectation and fit functions.

If the ‘silent’ flag is TRUE, then model execution will not print any status messages to the terminal.

If the ‘suppressWarnings’ flag is TRUE, then model execution will not issue a warning if NPSOL returns a non-zero status code.

If the 'unsafe' flag is TRUE, then many error conditions will not be detected. Any error condition detected will be downgraded to warnings. It is strongly recommended to use this feature only for debugging purposes.

Free parameters are estimated or updated based on the expectation and fit functions. These estimated values, along with estimation information and model fit, can be found in the 'output' slot of MxModel objects after mxRun has been used.

If a model is dependent on or shares parameters with another model, both models must be included as arguments in another MxModel object. This top-level MxModel object must include expectation and fit functions in both submodels, as well as an additional fit function describing how the results of the first two should be combined (e.g. [mxFitFunctionMultigroup](#)).

### Value

Returns an MxModel object with free parameters updated to their final values. The return value contains an "output" slot with the results of optimization.

### References

The OpenMx User's guide can be found at <https://openmx.ssri.psu.edu/documentation>.

### See Also

[mxTryHard](#) for running models which prove difficult to optimize; [summary](#) to print a summary of a run model; [mxModel](#) for more on the model itself; More information about the OpenMx package may be found [here](#).

### Examples

```
# Create and run the 1-factor CFA on the openmx.ssri.psu.edu front page

# 1. Load OpenMx and the demoOneFactor dataframe

library(OpenMx)
data(demoOneFactor)

# 2. Define the manifests (5 demo variables) and latents for use in the model

manifests <- names(demoOneFactor)
latents   <- c("G")

# 3. Build the model, adding paths and data
model <- mxModel(model="One Factor", type="RAM",
  manifestVars = manifests,
  latentVars   = latents,
  mxPath(from=latents, to=manifests, labels=paste("b", 1:5, sep="")),
  mxPath(from=manifests, arrows=2, labels=paste("u", 1:5, sep="")),
  mxPath(from=latents, arrows=2, free=FALSE, values=1.0),
  mxData(cov(demoOneFactor), type="cov", numObs=500)
)

# 4. Run the model, returning the result into model
```

```
model <- mxRun(model)

# 5. Show a summary of the fitted model and parameter values
summary(model)
```

---

mxSave

*Save End State to Checkpoint File*

---

## Description

The function saves the last state of a model to a checkpoint file.

## Usage

```
mxSave(model, chkpt.directory = ".", chkpt.prefix = "")
```

## Arguments

`model` [MxModel](#) object to be loaded.  
`chkpt.directory` character. Directory where the checkpoint file is located.  
`chkpt.prefix` character. Prefix of the checkpoint file.

## Details

In general, the arguments ‘`chkpt.directory`’ and ‘`chkpt.prefix`’ should be identical to the [mxOption](#): ‘`Checkpoint Directory`’ and ‘`Checkpoint Prefix`’ that were specified on the model before execution.

Alternatively, the checkpoint file can be manually loaded as a `data.frame` in R. Use [read.table](#) with the options `header=TRUE`, `sep="\t"`, `stringsAsFactors=FALSE`, `check.names=FALSE`.

## Value

Returns a logical indicating the succes of writing the checkpoint file to the checkpoint directory.

## References

The OpenMx User’s guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## Examples

```
library(OpenMx)

# Simulate some data

x=rnorm(1000, mean=0, sd=1)
y= 0.5*x + rnorm(1000, mean=0, sd=1)
```



```

tmpFrame <- data.frame(x, y)
tmpNames <- names(tmpFrame)

# Create a model that includes an expected covariance matrix,
# an expectation function, a fit function, and an observed covariance matrix

data <- mxData(cov(tmpFrame), type="cov", numObs = 1000)
expCov <- mxMatrix(type="Symm", nrow=2, ncol=2, values=c(.2,.1,.2), free=TRUE, name="expCov")
expFunction <- mxExpectationNormal(covariance="expCov", dimnames=tmpNames)
fitFunction <- mxFitFunctionML()
testModel <- mxModel(model="testModel", expCov, data, expFunction, fitFunction)

#Use mxRun to optimize the free parameters in the expected covariance matrix
modelOut <- mxRun(testModel)
modelOut$expCov

# Save the ending state of modelOut in a checkpoint file
mxSave(modelOut)

# Restore the saved model from the checkpoint file
modelSaved <- mxRestore(testModel)
modelSaved$expCov

# Imagine how much time you saved by not having to re-run the
# model that took hours or days to run.

```

---

mxSE

---

*Compute standard errors in OpenMx*


---

## Description

This function allows you to obtain standard errors for arbitrary expressions, named entities, and algebras.

## Usage

```

mxSE(x, model, details = FALSE, cov, forceName = FALSE, silent = FALSE,
     ..., defvar.row = 1L)

```

## Arguments

x	the parameter to get SEs on (reference or expression)
model	the <code>mxModel</code> to use.
details	logical. Whether to provide further details, e.g. the full sampling covariance matrix of x.
cov	optional matrix of covariances among the free parameters. If missing, the inverse Hessian from the fitted model is used.

forceName	logical; defaults to FALSE. Set to TRUE if x is an R symbol that refers to a character string.
silent	logical; defaults to FALSE. If TRUE, message-printing is suppressed.
...	further named arguments passed to <code>mxEval</code>
defvar.row	which row to load for any definition variables

### Details

x can be the name of an algebra, a bracket address, named entity or arbitrary expression. It is a frontend-only file that works much like `mxEval`. When the `details` argument is TRUE, the full sampling covariance matrix of x is also returned as part of a list. The square root of the diagonals of this sampling covariance matrix are the standard errors.

When supplying the `cov` argument, take care that the free parameter covariance matrix is given, not the information matrix. These two are inverses of one another.

### Value

SE value(s) returned as a matrix when `details` is FALSE. When `details` is TRUE, a list of the SE value(s) and the full sampling covariance matrix.

### References

- [https://en.wikipedia.org/wiki/Standard\\_error](https://en.wikipedia.org/wiki/Standard_error)

### See Also

- [mxCI](#)

### Examples

```
library(OpenMx)
data(demoOneFactor)
# =====
# = Make and run a 1-factor CFA =
# =====

latents = c("G") # the latent factor
manifests = names(demoOneFactor) # manifest variables to be modeled
# =====
# = Make and run the model! =
# =====
m1 <- mxModel("One Factor", type = "RAM",
  manifestVars = manifests, latentVars = latents,
  mxPath(from = latents, to = manifests, labels=paste0('lambda', 1:5)),
  mxPath(from = manifests, arrows = 2),
  mxPath(from = latents, arrows = 2, free = FALSE, values = 1),
  mxData(cov(demoOneFactor), type = "cov", numObs = 500)
)
m1 = mxRun(m1)
mxSE(lambda5, model = m1)
mxSE(lambda1^2, model = m1)
```

---

mxSetDefaultOptions     *Reset global options to the default*

---

**Description**

Reset global options to the default

**Usage**

```
mxSetDefaultOptions()
```

---

mxSimplify2Array     *Like simplify2array but works with vectors of different lengths*

---

**Description**

Vectors are filled column-by-column into a matrix. Shorter vectors are padded with NAs to fill whole columns.

**Usage**

```
mxSimplify2Array(x, higher = FALSE)
```

**Arguments**

x	a list of vectors
higher	whether to produce a higher rank array (defaults to FALSE)

**Examples**

```
v1 <- 1:3
v2 <- 4:5
v3 <- 6:10
mxSimplify2Array(list(v1,v2,v3))

#      [,1] [,2] [,3]
# [1,]  1   4   6
# [2,]  2   5   7
# [3,]  3  NA   8
# [4,] NA  NA   9
# [5,] NA  NA  10
```

---

mxStandardizeRAMpaths *Standardize RAM models' path coefficients*

---

### Description

Provides a dataframe containing the standardized values of all nonzero path coefficients appearing in the A and S matrices of models that use RAM expectation (either of type="RAM" or containing an explicit `mxExpectationRAM()` statement). These standardized values are what the path coefficients would be if all variables in the analysis—both manifest and latent—were standardized to zero mean and unit variance. If the means are being modeled in addition to the covariance structure, then the dataframe will also contain values of the nonzero elements of the M matrix after they have been re-scaled to standard deviation units. Can optionally include asymptotic standard errors for the standardized and re-scaled coefficients, computed via the delta method. Not intended for use with models that contain definition variables.

### Usage

```
mxStandardizeRAMpaths(model, SE=FALSE, cov=NULL)
```

### Arguments

model	An <code>mxModel</code> object, that either uses RAM expectation or contains at least one submodel that does.
SE	Logical. Should standard errors be included with the standardized point estimates? Defaults to FALSE. Certain conditions are required for use of SE=TRUE; see "Details" below.
cov	A repeated-sampling covariance matrix for the free-parameter estimates—say, from the robust "sandwich estimator," or from bootstrapping—used to calculate SEs for the standardized path coefficients. Defaults to NULL, in which case twice the inverse of the Hessian matrix at the ML solution is used. See below for details concerning cases when model contains independent RAM submodels.

### Details

Matrix A contains the Asymmetric paths, i.e. the single-headed arrows. Matrix S contains the Symmetric paths, i.e. the double-headed arrows. The function will work even if `mxMatrix` objects named "A" and "S" are absent from the model, since it identifies which matrices in the model have been assigned the roles of A and S in the `mxExpectationRAM` statement. Note that, in models of type="RAM", the necessary matrices and expectation statement are automatically assembled from the `mxPath` objects. If present, the M matrix will contain the means of exogenous variables and the intercepts of endogenous variables.

If model contains any submodels with `independent=TRUE` that use RAM expectation, `mxStandardizeRAMpaths()` automatically applies itself recursively over those submodels. However, if a non-NULL matrix has been supplied for argument cov, that matrix is only used for the "container" model, and is not passed

as argument to the recursive calls of the function. To provide a covariance matrix for calculating SEs in an independent submodel, use `mxStandardizeRAMpaths()` directly on that submodel.

Use of `SE=TRUE` requires that package `numDeriv` be installed. It also requires that model contain no `mxConstraint` statements. Finally, if `cov=NULL`, it requires model to have a nonempty hessian element in its output slot. There are three common reasons why the latter condition may not be met. First, the model may not have been run yet, i.e. it was not output by `mxRun()`. Second, `mxOption` "Hessian" might be set to "No". Third, computing the Hessian matrix might possibly have been skipped per a user-defined `mxCompute*` statement (if any are present in the model). If model contains RAM-expectation submodels with `independent=TRUE`, these conditions are checked separately for each such submodel.

In any event, using these standard errors for hypothesis-testing or forming confidence intervals is *not* generally advised. Instead, it is considered best practice to conduct likelihood-ratio tests or compute likelihood-based confidence intervals (from `mxCI()`), as in examples below.

The user should note that `mxStandardizeRAMpaths()` only cares whether an element of A or S (or M) is nonzero, and not whether it is a fixed or free parameter. So, for instance, if the function is used on a model not yet run, any free parameters in A or S initialized at zero will not appear in the function's output.

**The user is warned** to interpret the output of `mxStandardizeRAMpaths()` cautiously if any elements of A or S depend upon "definition variables" (you have definition variables in your model if the labels of any `MxPath` or `MxMatrix` begin with "data. "). Typically, either `mxStandardizeRAMpaths()`'s results will be valid only for the first row of the raw dataset (and any rows identical to it), or some of the standardized coefficients will be incorrectly reported as zero.

## Value

If argument `model` is a single-group model that uses RAM expectation, then `mxStandardizeRAMpaths()` returns a dataframe, with one row for each nonzero path coefficient in A and S (and M, if present), and with the following columns:

<code>name</code>	Character strings that uniquely identify each nonzero path coefficient in terms of the model name, the matrix ("A", "S", or "M"), the row number, and the column number.
<code>label</code>	Character labels for those path coefficients that are labeled elements of an <code>mxMatrix</code> object, and NA for those that are not. Note that path coefficients having the same label (and therefore the same UNstandardized value) can have different standardized values, and therefore the same label may appear more than once in this dataframe.
<code>matrix</code>	Character strings of "A", "S", or "M", depending on which matrix contains the given path coefficient.
<code>row</code>	Character. The rownames of the matrix containing each path coefficient; row numbers are used instead if the matrix has no rownames.
<code>col</code>	Character. The colnames of the matrix containing each path coefficient; column numbers are used instead if the matrix has no colnames.
<code>Raw.Value</code>	Numeric values of the raw (i.e., UNstandardized) path coefficients.
<code>Raw.SE</code>	Numeric values of the asymptotic standard errors of the raw path coefficients if <code>SE=TRUE</code> , or "not_requested" otherwise.

Std.Value	Numeric values of the standardized path coefficients.
Std.SE	Numeric values of the asymptotic standard errors of the standardized path coefficients if SE=TRUE, or "not_requested" otherwise.

If model is a multi-group model containing at least one submodel with RAM expectation, then mxStandardizeRAMpaths() returns a list. The list has a number of elements equal to the number of submodels that either have RAM expectation or contain a submodel that does. List elements corresponding to RAM-expectation submodels contain a dataframe, as described above. List elements corresponding to "container" submodels are themselves lists, of the kind described here.

### See Also

[mxBootstrapStdizeRAMpaths\(\)](#)

### Examples

```
library(OpenMx)
data(demoOneFactor)
manifests <- names(demoOneFactor)
latents <- c("G")
factorModel <- mxModel(model="One Factor", type="RAM",
  manifestVars = manifests,
  latentVars = latents,
  mxPath(from=latents, to=manifests),
  mxPath(from=manifests, arrows=2, values=0.1),
  mxPath(from=latents, arrows=2, free=FALSE, values=1.0),
  mxData(cov(demoOneFactor), type="cov", numObs=500)
)
factorFit <- mxRun(factorModel)
summary(factorFit)$parameters
mxStandardizeRAMpaths(model=factorFit, SE=FALSE)

## Likelihood ratio test of variable x1's factor loading:
factorModelNull <- omxSetParameters(factorModel, labels="One Factor.A[1,6]",
  values=0, free=FALSE)
factorFitNull <- mxRun(factorModelNull)
mxCompare(factorFit, factorFitNull)[2, "p"] #<--p-value

## Confidence intervals for all standardized paths:
factorModel2 <- mxModel(model=factorModel,
  mxMatrix(type="Iden", nrow=nrow(factorModel$A), name="I"),
  mxAlgebra( vec2diag(diag2vec( solve(I-A)%*%S%*t(solve(I-A)) )%^-0.5) ,
    name="InvSD"),
  mxAlgebra( InvSD %*% A %*% solve(InvSD),
    name="Az", dimnames=dimnames(factorModel$A)),
  mxAlgebra( InvSD %*% S %*% InvSD,
    name="Sz", dimnames=dimnames(factorModel$S)),
  mxCI(c("Az", "Sz"))
)
## Not run:
factorFit2 <- mxRun(factorModel2, intervals=TRUE)
## Contains point values and confidence limits for all paths:
```

```
summary(factorFit2)$CI
## End(Not run)
```

---

mxThreshold

*Create List of Thresholds*


---

## Description

This function creates a list of thresholds which mxModel can use to set up a thresholds matrix for a RAM model.

## Usage

```
mxThreshold(vars, nThresh=NA,
            free=FALSE, values=NA, labels=NA,
            lbound=NA, ubound=NA)
```

## Arguments

vars	character vector. These are the variables for which thresholds are to be specified.
nThresh	numeric vector. These are the number of thresholds for each variables listed in 'vars'.
free	boolean vector. Indicates whether threshold parameters are free or fixed.
values	numeric vector. The starting values of the parameters.
labels	character vector. The names of the parameters.
lbound	numeric vector. The lower bounds of free parameters.
ubound	numeric vector. The upper bounds of free parameters.

## Details

If you are new to ordinal data modeling and just want something quick to make your ordinal data work, we recommend you try the [umxThresholdMatrix](#) function in the umx package.

The mxPath function creates [MxThreshold](#) objects. These consist of a list of ordinal variables and the thresholds that define the relationship between the observed ordinal variable and the continuous latent variable assumed to underly it. This function directly mirrors the usage of [mxPath](#), but is used to specify thresholds rather than means, variances and bivariate relationships.

The 'vars' argument specifies which variables you wish to specify thresholds for. Variables are referenced by name, and these names must appear in the 'manifestVar' argument of the [mxModel](#) function if thresholds are to be correctly processed. Additionally, variables for which thresholds are specified must be specified as ordinal factors in whatever data is included in the model.

The 'nThresh' argument specifies how many thresholds are to be specified for the variable or variables included in the 'vars' argument. The number of thresholds for a particular variable should be one fewer than the number of categories specified for that variable.

The 'free' argument specifies whether the thresholds created by the mxThreshold function are free or fixed parameters. This argument may take either TRUE for free parameters, FALSE for fixed parameters, or a vector of TRUEs and FALSEs to be applied in order to the created thresholds.

'values' is a numeric vector containing the starting values of the created thresholds. This gives a starting point for estimation. The 'labels' argument specifies the names of the parameters in the resulting MxThreshold object. The 'lbound' and 'ubound' arguments specify lower and upper bounds for the created threshold parameters.

Thresholds for multiple variables may be specified simultaneously by including a vector of variable names to the 'vars' argument. When multiple variables are included in the 'vars' argument, the length of the 'vars' argument must be evenly divisible by the length of the 'nThresh' argument. All subsequent arguments ('free' through 'ubound') should have their lengths be a factor of the total number of thresholds specified for all variables.

If four variables are included in the 'vars' argument, then the 'nThresh' argument should contain either one, two or four elements. If the 'nThresh' argument specifies two thresholds for each variable, then 'free', 'values', and all subsequent arguments should specify eight values by including one, two, four or eight elements. Whenever fewer values are specified than are required (e.g., specify two values for eight thresholds), then the entire vector of values is repeated until the required number of values is reached, and will return an error if the correct number of values cannot be achieved by repeating the entire vector.

## Value

Returns a list of thresholds.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

[umxThresholdMatrix](#) `demo("mxThreshold")` [mxPath](#) for comparable specification of paths. [mxMatrix](#) for a matrix-based approach to thresholds specification; [mxModel](#) for the container in which mxThresholds are embedded. More information about the OpenMx package may be found [here](#).

## Examples

```
library(OpenMx)
# threshold objects for three variables: 2 binary, and one ordinal.
mxThreshold(vars = c("z1", "z2", "z3"), nThresh = c(1,1,2),
  free = TRUE, values = c(-1, 0, -.5, 1.2) )
```



---

 mxTryHard

*Make multiple attempts to run a model*


---

## Description

Makes multiple attempts to fit an MxModel object with `mxRun()` until the optimizer yields an acceptable solution or the maximum number of attempts is reached. Between attempts, start values are perturbed by random numbers, and optimization-control parameters may be altered. From among its attempts, the function returns the fitted, post-`mxRun()` model with the smallest fit-function value, and can print to the console the start values it used for that model.

## Usage

```
mxTryHard(model, extraTries = 10, greenOK = FALSE, loc = 1, scale = 0.25,
  initialGradientStepSize = imxAutoOptionValue("Gradient step size"),
  initialGradientIterations = imxAutoOptionValue('Gradient iterations'),
  initialTolerance=as.numeric(mxOption(NULL, 'Optimality tolerance')),
  checkHess = TRUE, fit2beat = Inf, paste = TRUE, iterationSummary=FALSE,
  bestInitsOutput=TRUE, showInits=FALSE, verbose=0, intervals = FALSE,
  finetuneGradient=TRUE, jitterDistrib=c("runif", "rnorm", "rcauchy"), exhaustive=FALSE,
  maxMajorIter=3000, OKstatuscodes, wtgcsv=c("prev", "best", "initial"), silent=interactive())
```

```
mxTryHardOrig(model, finetuneGradient=FALSE, maxMajorIter=NA,
  wtgcsv=c("prev", "best"), silent=FALSE, ...)
```

```
mxTryHardctsem(model, initialGradientStepSize = .00001,
  initialGradientIterations = 1,
  initialTolerance=1e-12, jitterDistrib="rnorm", ...)
```

```
mxTryHardWideSearch(model, finetuneGradient=FALSE, jitterDistrib="rcauchy",
  exhaustive=TRUE, wtgcsv="prev", ...)
```

```
mxTryHardOrdinal(model, greenOK = TRUE, checkHess = FALSE,
  finetuneGradient=FALSE, exhaustive=TRUE,
  OKstatuscodes=c(0,1,5,6), wtgcsv=c("prev", "best"), ...)
```

## Arguments

<code>model</code>	The MxModel to be run.
<code>extraTries</code>	The number of attempts to run the model <i>in addition to the first</i> . In effect, is the maximum number of attempts <code>mxTryHard()</code> will make, since the function will stop once an acceptable solution is reached. Defaults to 10 (for <code>mxTryHard()</code> ), in which case a maximum of 11 total attempts will be made.
<code>greenOK</code>	Logical; is a solution with Mx status GREEN (optimizer status code 1) acceptable? Defaults to FALSE (for <code>mxTryHard()</code> ). Ignored if a value is provided for <code>OKstatuscodes</code> .

loc, scale	Numeric. The location and scale parameters of the distribution from which random values are drawn to perturb start values between attempts, defaulting respectively to 1 and 0.25. See below, under "Details," for additional information.
initialGradientStepSize, initialGradientIterations, initialTolerance	Numeric. Initial values of optimization-control parameters passed to <code>mxComputeGradientDescent()</code> if model is using the default compute plan.
checkHess	Logical; is a positive-definite Hessian a requirement for an acceptable solution? Defaults to TRUE (for <code>mxTryHard()</code> ). If TRUE, the Hessian and standard errors are calculated with each fit attempt, irrespective of the value of relevant <code>options</code> . The exception is if model or any of its submodels contains <code>MxConstraints</code> , in which case <code>checkHess</code> is coerced to FALSE.
fit2beat	Numeric upper limit to the fitfunction value that an acceptable solution may have. Useful if a nested submodel of model has already been fitted, since model, with its additional free parameters, should not yield a fitfunction value any greater than that of the submodel.
paste	Logical. If TRUE (default), start values for the returned fitted model are printed to console as a comma-separated string. This is useful if the user wants to copy-paste these values into an R script, say, in an <code>omxSetParameters()</code> statement. If FALSE, the vector of start values is printed as-is. Note that this vector, from <code>omxGetParameters()</code> , has names corresponding to the free parameters; these names are not displayed when <code>paste=TRUE</code> .
iterationSummary	Logical. If TRUE, displays parameter estimates and fit values for every fit attempt, even if <code>silent=TRUE</code> . Defaults to FALSE.
bestInitsOutput	Logical. If TRUE and if <code>silent=FALSE</code> , <code>mxTryHard()</code> displays the starting values that resulted in the best fit, according to format specified by <code>paste</code> argument. Defaults to TRUE.
showInits	Logical. If TRUE, displays starting values for every fit attempt, even if <code>silent=TRUE</code> . Defaults to FALSE.
verbose	If model is using the default compute plan, is passed to <code>mxComputeGradientDescent()</code> to specify level of output printed to console during optimization.
intervals	Logical. If TRUE, OpenMx will estimate any specified confidence intervals.
finetuneGradient	Logical. If TRUE (default for <code>mxTryHard()</code> ), then as repeated fit attempts appear to be improving, <code>mxTryHard()</code> will adjust optimization-control parameters <code>gradientStepSize</code> , <code>gradientIterations</code> , and <code>tolerance</code> , as well as argument <code>scale</code> , to "fine-tune" its convergence toward an optimal solution. <code>finetuneGradient=FALSE</code> is recommended for analyses involving thresholds.
jitterDistrib	Character string naming which random-number distribution—either <code>uniform (rectangular)</code> , <code>normal (Gaussian)</code> , or <code>Cauchy</code> —to be used to perturb start values. Defaults to the uniform distribution (for <code>mxTryHard()</code> ). See below, under "Details," for additional information.
exhaustive	Logical. If FALSE (default for <code>mxTryHard()</code> ), <code>mxTryHard()</code> stops making additional attempts once it reaches an acceptable solution. If TRUE, the function instead continues until it reaches its maximum number of attempts (as per <code>extraTries</code> ), and returns the best solution it found.

maxMajorIter	Integer; passed to <code>mxComputeGradientDescent()</code> . Defaults to 3000, which was the internally hardcoded value <code>mxTryHard()</code> used in at least one prior version of OpenMx. Value of NA is permitted, in which case <code>mxTryHard()</code> will calculate a value via the on-load default formula for the "Major iterations" option.
OKstatuscodes	Optional integer vector containing optimizer status codes that an acceptable solution is permitted to have. <code>mxTryHard()</code> always considers a status code of 0 to be acceptable, this argument notwithstanding. By default, <code>mxTryHard()</code> will consider status code 0 acceptable, and, if <code>greenOK=TRUE</code> , status code 1 as well. If a value is supplied for <code>OKstatuscodes</code> that conflicts with <code>greenOK</code> , <code>OKstatuscodes</code> controls.
wtgcsv	Character vector. "Where to get current start values." See below, under "Details," for additional information.
silent	Logical; for <code>mxTryHard()</code> , defaults to TRUE if running interactively, and to FALSE otherwise. If TRUE, persistent <a href="#">message-printing</a> during execution of <code>mxTryHard()</code> is suppressed, and non-persistent printing is used instead. The two exceptions are the persistent printing requested by TRUE values of <code>iterationSummary</code> and <code>showInits</code> .
...	Additional arguments to be passed to <code>mxTryHard()</code> .

## Details

`mxTryHardOrig()`, `mxTryHardctsem()`, `mxTryHardWideSearch()`, and `mxTryHardOrdinal()` are wrapper functions to the main workhorse function `mxTryHard()`. Each wrapper function has default values for certain arguments that are tailored toward a specific purpose. `mxTryHardOrig()` imitates the functionality of the earliest implementations of `mxTryHard()` in OpenMx's history; its chief purpose is to find good start values that lead to an acceptable solution. `mxTryHardctsem()` uses `mxTryHard()` to "zero in" on an acceptable solution with models that can be difficult to optimize, such as continuous-time state-space models. `mxTryHardWideSearch()` uses `mxTryHard()` to search a wide region of the parameter space, in hope of avoiding local fitfunction minima. `mxTryHardOrdinal()` attempts to use `mxTryHard()` as well as it can be used with models involving ordinal data.

Argument `wtgcsv` dictates where `mxTryHard()` is permitted to find free-parameter values, at the start of each fit attempt after the first, before randomly perturbing them to create the current fit attempt's start values. If "prev" is included, then `mxTryHard()` is permitted to use the parameter estimates of the most recent non-error fit attempt. If "best" is included, then `mxTryHard()` is permitted to use the parameter estimates at the best solution so far. If "initial" is included, then `mxTryHard()` is permitted to use the initial start values in `model`, as provided by the user. The default is to permit all three, in which case `mxTryHard()` is written to use the best solution's values if available, and otherwise to use the most recent solution's values, but to periodically revert to the initial values if recent fit attempts have not improved on the best solution.

Once the start values are located for the current fit attempt, they are randomly perturbed before being assigned to the `MxModel`. The distributional family from which the perturbations are randomly generated is dictated by argument `jitterDistrib`. The distribution is parametrized by arguments `loc` and `scale`, respectively the location and scale parameters. The location parameter is the distribution's median. For the uniform distribution, `scale` is the absolute difference between its median and extrema (i.e., half the width of the rectangle); for the normal distribution, `scale` is its standard

deviation; and for the Cauchy, scale is one-half its interquartile range. Start values are first multiplied by random draws from a distribution with the provided loc and scale, then added to random draws from a distribution with the same scale but with a median of zero.

### Value

Usually, `mxTryHard()` returns a post-`mxRun()` `MxModel` object. Specifically, this will be the fitted model having the smallest fit-function value found by `mxTryHard()` during its attempts. The start values used to obtain this fitted model are printed to console if `bestInitsOutput=TRUE`.

If every attempt at running model fails, `mxTryHard()` returns an object of class 'try-error'.

`mxTryHard()` throws a warning if the returned `MxModel` object has a nonzero status code (unless nonzero status codes are considered acceptable per argument `greenOK` or `OKstatuscodes`).

### See Also

`mxRun()`, `mxComputeTryHard`

### Examples

```
library(OpenMx)

data(demoOneFactor) # load the demoOneFactor dataframe

manifests <- names(demoOneFactor) # set the manifest to the 5 demo variables
latents  <- c("G") # define 1 latent variable
model <- mxModel(model="One Factor", type="RAM",
  manifestVars = manifests,
  latentVars   = latents,
  mxPath(from=latents, to=manifests, labels=paste("b", 1:5, sep="")),
  mxPath(from=manifests, arrows=2, labels=paste("u", 1:5, sep="")),
  mxPath(from=latents , arrows=2, free=FALSE, values=1.0),
  mxData(cov(demoOneFactor), type="cov", numObs=500)
)
model <- mxTryHard(model) # Run the model, returning the result into model
summary(model) # Show summary of the fitted model
```

---

mxTypes

*List Currently Available Model Types*

---

### Description

This function returns a vector of the currently available type names.

### Usage

```
mxTypes()
```

**Value**

Returns a character vector of type names.

**Examples**

```
mxTypes()
```

---

mxVersion	<i>Returns Current Version String</i>
-----------	---------------------------------------

---

**Description**

This function returns a string with the current version number of OpenMx. Optionally (with `verbose = TRUE` (the default)), it prints a message containing the version of R, the platform, and the optimiser.

**Usage**

```
mxVersion(model = NULL, verbose = TRUE)
```

**Arguments**

model	optional <a href="#">MxModel</a> to request optimizer from (default = NULL)
verbose	Whether to print version information to the console (default = TRUE)

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
# Print useful version information.
mxVersion()
# If you just want the version, use this call.
x = mxVersion(verbose=FALSE)

library(OpenMx)
data(demoOneFactor) # load the demoOneFactor dataframe
manifests <- names(demoOneFactor) # set the manifest to the 5 demo variables
latents <- c("G") # define 1 latent variable
model <- mxModel(model = "One Factor", type = "RAM",
  manifestVars = manifests,
  latentVars = latents,
  mxPath(from = latents, to = manifests, labels = paste("b", 1:5, sep = "")),
  mxPath(from = manifests, arrows = 2, labels = paste("u", 1:5, sep = "")),
  mxPath(from = latents, arrows = 2, free = FALSE, values = 1.0),
  mxData(cov(demoOneFactor), type = "cov", numObs = 500))
```

```
)  
mxVersion(model, verbose = TRUE)
```

---

MxVersionType-class    *A package\_version or character*

---

### Description

A package\_version or character

---

myAutoregressiveData    *Example data with autoregressively related columns*

---

### Description

Data set used in some of OpenMx's examples.

### Usage

```
data("myAutoregressiveData")
```

### Format

A data frame with 100 observations on the following variables.

x1 x variable and time 1  
x2 x variable and time 2  
x3 x variable and time 3  
x4 x variable and time 4  
x5 x variable and time 5

### Details

The rows are independently and identically distributed, but the columns are and auto-correlation structure.

### Source

Simulated.

### References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```

data(myAutoregressiveData)
round(cor(myAutoregressiveData), 2)
# note the sub-diagonal correlations (lag 1)
# x1-x2, x2-x3, x3-x4, x4-x5
# and the second sub-diagonal correlations (lag 2)
# x1-x3, x2-x4, x3-x5

```

---

myFADDataRaw

*Example 500-row dataset with 12 generated variables*


---

**Description**

Twelve columns of generated numeric data: x1 x2 x3 x4 x5 x6 y1 y2 y3 z1 z2 z3.

**Usage**

```
data(myFADDataRaw)
```

**Details**

The x variables intercorrelate around .6 with each other.

The y variables intercorrelate around .5 with each other, and correlate around .3 with the X vars.

There are three ordinal variables, z1, z2, and z3.

The data are used in some OpenMx examples, especially confirmatory factor analysis.

There are no missing data.

**Examples**

```

data(myFADDataRaw)
str(myFADDataRaw)

```

---

myGrowthKnownClassData

*Data for a growth mixture model with the true class membership*


---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("myGrowthKnownClassData")
```

**Format**

A data frame with 500 observations on the following variables.

x1 x variable and time 1

x2 x variable and time 2

x3 x variable and time 3

x4 x variable and time 4

x5 x variable and time 5

c Known class membership variable

**Details**

The same as [myGrowthMixtureData](#), but with the class membership variable.

**Source**

Simulated.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(myGrowthKnownClassData)

#plot the observed trajectories
# blue lines are class 1, green lines are class 2
colSel <-c('blue', 'green')[myGrowthKnownClassData$c]
matplot(t(myGrowthKnownClassData[,-6]), type='l', lty=1, col=colSel)
```

---

myGrowthMixtureData    *Data for a growth mixture model*

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("myGrowthMixtureData")
```



**Format**

A data frame with 500 observations on the following variables.

x1 x variable and time 1

x2 x variable and time 2

x3 x variable and time 3

x4 x variable and time 4

x5 x variable and time 5

**Details**

The same as [myGrowthKnownClassData](#), but without the class membership variable.

**Source**

Simulated.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(myGrowthMixtureData)

matplot(t(myGrowthMixtureData), type='l', lty=1)

data(myGrowthKnownClassData)
all(myGrowthKnownClassData[, -6]==myGrowthMixtureData)
```

---

myLongitudinalData      *Data for a linear latent growth curve model*

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("myLongitudinalData")
```

**Format**

A data frame with 500 observations on the following variables.

x1 x variable and time 1

x2 x variable and time 2

x3 x variable and time 3

x4 x variable and time 4

x5 x variable and time 5

**Details**

Linear growth model with mean intercept around 10, and slope of about 1.5.

**Source**

Simulated.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(myLongitudinalData)
```

```
matplot(t(myLongitudinalData), type='l', lty=1)
```

---

myRegData

*Example regression data with correlated predictors*

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("myRegData")
```

**Format**

A data frame with 100 observations on the following variables.

w Predictor variable

x Predictor variable

y Predictor variable

z Outcome variable

**Details**

w, x, and y are predictors of z. x and y are correlated.

**Source**

Simulated.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(myRegData)
summary(lm(z ~ ., data=myRegData))
```

---

myRegDataRaw

*Example regression data with correlated predictors*

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("myRegDataRaw")
```

**Format**

A data frame with 100 observations on the following variables.

w Predictor variable  
x Predictor variable  
y Predictor variable  
z Outcome variable

**Details**

w, x, and y are predictors of z. x and y are correlated. Equal to [myRegData](#).

**Source**

Simulated.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(myRegData)
data(myRegDataRow)

all(myRegDataRow == myRegData)
```

---

myTwinData

*Twin data on weight and height*

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("myTwinData")
```

**Format**

A data frame with 3808 observations on the following variables.

fam Family ID variable  
age Age of the twin pair. Range: 17 to 88.  
zyg Integer codes for zygosity and gender combinations  
part  
wt1 Weight in kilograms for twin 1  
wt2 Weight in kilograms for twin 2  
ht1 Height in meters for twin 1  
ht2 Height in meters for twin 2  
htwt1 Product of ht and wt for twin 1  
htwt2 Product of ht and wt for twin 2  
bmi1 Body Mass Index for twin 1  
bmi2 Body Mass Index for twin 2

**Details**

Height and weight are highly correlated, and each individually highly heritable. These data present and opportunity for multivariate behavior genetics modeling.

**Source**

Timothy Bates

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(myTwinData)
```

```
plot( ht1 ~ wt1, myTwinData)
```

---

mzfData

*MZ female example twin data*

---

**Description**

Data for extended twin example ETC88.R

**Usage**

```
data("mzfData")
```

**Format**

A data frame with 3099 observations on the following 37 variables.

famid a numeric vector

e1 a numeric vector

e2 a numeric vector

e3 a numeric vector

e4 a numeric vector

e5 a numeric vector

e6 a numeric vector

e7 a numeric vector

e8 a numeric vector

e9 a numeric vector

e10 a numeric vector

e11 a numeric vector

e12 a numeric vector

e13 a numeric vector

e14 a numeric vector

e15 a numeric vector

e16 a numeric vector

e17 a numeric vector  
e18 a numeric vector  
a1 a numeric vector  
a2 a numeric vector  
a3 a numeric vector  
a4 a numeric vector  
a5 a numeric vector  
a6 a numeric vector  
a7 a numeric vector  
a8 a numeric vector  
a9 a numeric vector  
a10 a numeric vector  
a11 a numeric vector  
a12 a numeric vector  
a13 a numeric vector  
a14 a numeric vector  
a15 a numeric vector  
a16 a numeric vector  
a17 a numeric vector  
a18 a numeric vector

### Examples

```
data(mzfData)  
str(mzfData)
```

---

mzmData

*MZ Male example data*

---

### Description

Data for extended twin example ETC88.R

### Usage

```
data("mzmData")
```

**Format**

A data frame with 3019 observations on the following 37 variables.

famid a numeric vector

e1 a numeric vector

e2 a numeric vector

e3 a numeric vector

e4 a numeric vector

e5 a numeric vector

e6 a numeric vector

e7 a numeric vector

e8 a numeric vector

e9 a numeric vector

e10 a numeric vector

e11 a numeric vector

e12 a numeric vector

e13 a numeric vector

e14 a numeric vector

e15 a numeric vector

e16 a numeric vector

e17 a numeric vector

e18 a numeric vector

a1 a numeric vector

a2 a numeric vector

a3 a numeric vector

a4 a numeric vector

a5 a numeric vector

a6 a numeric vector

a7 a numeric vector

a8 a numeric vector

a9 a numeric vector

a10 a numeric vector

a11 a numeric vector

a12 a numeric vector

a13 a numeric vector

a14 a numeric vector

a15 a numeric vector

a16 a numeric vector

a17 a numeric vector

a18 a numeric vector

**Examples**

```
data(mzmData)
str(mzmData)
```

---

Named-entity

*Named Entities*

---

**Description**

A named entity is an S4 object that can be referenced by name.

**Details**

Every named entity is guaranteed to have a slot called "name". Within a model, the named entities of that model can be accessed using the \$ operator. Access is limited to one nesting depth, such that if 'B' is a submodel of 'A', and 'C' is a matrix of 'B', then 'C' must be accessed using A\$B\$C.

The following S4 classes are named entities in the OpenMx library: [MxAlgebra](#), [MxConstraint](#), [MxMatrix](#), [MxModel](#), [MxData](#), and [MxObjective](#).

**Examples**

```
library(OpenMx)

# Create a model, add a matrix to it, and then access the matrix by name.

testModel <- mxModel(model="anEmptyModel")

testMatrix <- mxMatrix(type="Full", nrow=2, ncol=2, values=c(1,2,3,4), name="yourMatrix")

yourModel <- mxModel(testModel, testMatrix, name="noLongerEmpty")

yourModel$yourMatrix
```

---

nuclear\_twin\_design\_data

*Twin data from a nuclear family design*

---

**Description**

Data set used in some of OpenMx's examples.



**Usage**

```
data("nuclear_twin_design_data")
```

**Format**

A data frame with 1743 observations on the following variables.

Twin1

Twin2

Father

Mother

zyg Zygoty of the twin pair

**Details**

This is a wide format data set. A single variable has values for different member of the same nuclear family.

**Source**

Likely simulated.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(nuclear_twin_design_data)
```

```
cor(nuclear_twin_design_data[,-5], use="pairwise.complete.obs")
```

---

numHess1

*numeric Hessian data 1*

---

**Description**

data file used by the HessianTest.R script

**Usage**

```
data("numHess1")
```

**Format**

A 12 by 12 data frame containing Hessian (numeric variables a-l)

**Examples**

```
data(numHess1)
str(numHess1)
```

---

numHess2	<i>numeric Hessian data 2</i>
----------	-------------------------------

---

**Description**

data file used by the HessianTest.R script

**Usage**

```
data("numHess2")
```

**Format**

A 12 by 12 data frame containing Hessian matrix (numeric variables a-l)

**Examples**

```
data(numHess2)
str(numHess2)
```

---

omxAllInt	<i>All Interval Multivariate Normal Integration</i>
-----------	---

---

**Description**

omxAllInt computes the probabilities of a large number of cells of a multivariate normal distribution that has been sliced by a varying number of thresholds in each dimension. While the same functionality can be achieved by repeated calls to [omxMnor](#), omxAllInt is more efficient for repeated operations on a single covariance matrix. omxAllInt returns an nx1 matrix of probabilities cycling from lowest to highest thresholds in each column with the rightmost variable in *covariance* changing most rapidly.

**Usage**

```
omxAllInt(covariance, means, ...)
```

**Arguments**

covariance	the covariance matrix describing the multivariate normal distribution.
means	a row vector containing means of the variables of the underlying distribution.
...	a matrix or set of matrices containing one column of thresholds for each column of covariance. Each column must contain a strictly increasing set of thresholds for the corresponding variable of the underlying distribution. NA values in these thresholds indicate that the list of thresholds in that column has ended.

## Details

*covariance* and *means* contain the covariances and means of the multivariate distribution from which probabilities are to be calculated.

*covariance* must be a square covariance or correlation matrix with one row and column for each variable.

*means* must be a vector of length `nrows(covariance)` that contains the mean for each corresponding variable.

All further arguments are considered threshold matrices.

Threshold matrices contain locations of the hyperplanes delineating the intervals to be calculated. The first column of the first matrix corresponds to the thresholds for the first variable represented by the covariance matrix. Subsequent columns of the same matrix correspond to thresholds for subsequent variables in the covariance matrix. If more variables exist in the covariance matrix than in the first threshold matrix, the first column of the second threshold matrix will be used, and so on. That is, if *covariance* is a 4x4 matrix, and the three threshold matrices are specified, one with a single column and the others with two columns each, the first column of the first matrix will contain thresholds for the first variable in *covariance*, the two columns of the second matrix will correspond to the second and third variables of *covariance*, respectively, and the first column of the third threshold matrix will correspond to the fourth variable. Any extra columns will be ignored.

Each column in the threshold matrices must contain some number of strictly increasing thresholds, delineating the boundaries of a cell of integration. That is, if the integral from -1 to 0 and 0 to 1 are required for a given variable, the corresponding threshold column should contain the values -1, 0, and 1, in that order. Thresholds may be set to `Inf` or `-Inf` if a boundary at positive or negative infinity is desired.

Within a threshold column, a value of `+Inf`, if it exists, is assumed to be the largest threshold, and any rows after it are ignored in that column. A value of `NA`, if it exists, indicates that there are no further thresholds in that column, and is otherwise ignored. A threshold column consisting of only `+Inf` or `NA` values will cause an error.

For all  $i > 1$ , the value in row  $i$  must be strictly larger than the value in row  $i-1$  in the same column.

The return value of `omxAllInt` is a matrix consisting of a single column with one row for each combination of threshold levels.

## See Also

[omxMnor](#)

## Examples

```
data(myFADDataRaw)

covariance <- cov(myFADDataRaw[,1:5])
means <- colMeans(myFADDataRaw[,1:5])

# Integrate from -Infinity to 0 and 0 to 1 on first variable
thresholdForColumn1 <- cbind(c(-Inf, 0, 1))
# Note: The first variable will never be calculated from 1 to +Infinity.
```

```

# These columns will be integrated from -Inf to -1, -1 to 0, etc.
thresholdsForColumn2 <- cbind(c(-Inf, -1, 0, 1, Inf))
thresholdsForColumns3and4 <- cbind(c(-Inf, 1.96, 2.326, Inf),
                                   c(-Inf, -1.96, 2.326, Inf))

# The integration
omxAllInt(covariance, means,
          thresholdForColumn1, thresholdsForColumn2,
          thresholdsForColumns3and4, thresholdsForColumn2)
# Notice that columns 2 and 5 are assigned identical thresholds.

#-----
# An alternative specification of the same calculation follows
covariance <- cov(myFADDataRaw[,1:5])
means <- colMeans(myFADDataRaw[,1:5])

# Note NAs to indicate the end of the sequence of thresholds.
thresholds <- cbind(c(-Inf, 0, 1, NA, NA),
                   c(-Inf, -1, 0, 1, Inf),
                   c(-Inf, 1.96, 2.32, Inf, NA),
                   c(-Inf, -1.96, 2.32, Inf, NA),
                   c(-Inf, -1, 0, 1, Inf))
omxAllInt(covariance, means, thresholds)

```

---

omxApply

*On-Demand Parallel Apply*


---

## Description

If the snowfall library is loaded, then this function calls [sfApply](#). Otherwise it invokes [apply](#).

## Usage

```
omxApply(x, margin, fun, ...)
```

## Arguments

x	a vector (atomic or list) or an expressions vector. Other objects (including classed objects) will be coerced by <a href="#">as.list</a> .
margin	a vector giving the subscripts which the function will be applied over.
fun	the function to be applied to each element of x.
...	optional arguments to fun.

## See Also

[omxLapply](#), [omxSapply](#)

**Examples**

```
x <- cbind(x1 = 3, x2 = c(4:1, 2:5))
dimnames(x)[[1]] <- letters[1:8]
omxApply(x, 2, mean, trim = .2)
```

---

```
omxAssignFirstParameters
```

*Assign First Available Values to Model Parameters*

---

**Description**

Sometimes you may have a free parameter with two different starting values in your model. OpenMx will not run a model until all instances of a free parameter have the same starting value. It is often sufficient to arbitrarily select one of those starting values for optimization.

This function accomplishes that task of assigning valid starting values to the free parameters of a model. It selects an arbitrary current value (the "first" value it finds, where "first" is not defined) for each free parameter and uses that value for all instances of that parameter in the model.

**Usage**

```
omxAssignFirstParameters(model, indep = FALSE)
```

**Arguments**

model	a MxModel object.
indep	assign parameters to independent submodels.

**See Also**

[omxGetParameters](#), [omxSetParameters](#)

**Examples**

```
A <- mxMatrix('Full', 3, 3, values = c(1:9), labels = c('a','b', NA),
              free = TRUE, name = 'A')
model <- mxModel(model=A, name = 'model')
model <- omxAssignFirstParameters(model)

# Note: All cells with the same label now have the same start value.
# Note also that NAs are untouched.

model$matrices$A

# $labels
#      [,1] [,2] [,3]
```

```

# [1,] "a" "a" "a"
# [2,] "b" "b" "b"
# [3,] NA  NA  NA
#
# $values
#      [,1] [,2] [,3]
# [1,]   1   1   1
# [2,]   2   2   2
# [3,]   3   6   9

```

---

omxBrownie

*Make Brownies in OpenMx*


---

## Description

This function returns a brownie recipe.

## Usage

```
omxBrownie(quantity=1, walnuts=TRUE)
```

## Arguments

quantity	Number of batches of brownies desired. Defaults to one.
walnuts	Logical. Indicates whether walnuts are to be included in the brownies. Defaults to TRUE.

## Details

Returns a brownie recipe. Alter the ‘quantity’ variable to make more pans of brownies. Ingredients, equipment and procedure are listed, but neither ingredients nor equipment are provided.

Raw cocoa powder can be used instead of Dutch processed cocoa for approximately double the antioxidants and flavonols. However, raw cocoa powder is not as smooth and delicious in taste.

We substitute coconut butter for dairy butter because dairy butter contains a large proportion of saturated fat that raises deadly LDL cholesterol (Trumbo & Shimakawa, 2011). In contrast, coconut butter has so much fiber that the considerable saturated fat that it contains is mostly not absorbed (Padmakumaran, Rajamohan & Kurup, 1999). You can substitute erythritol (den Hartog et al, 2010) for sucanat (Lustig, Schmidt, & Brindis, 2012) to improve the glycemic index and calorie density. We substitute whole wheat flour for all-purpose wheat flour because whole grains are associated with improvement in blood pressure (Tighe et al, 2010).

## Value

Returns a brownie recipe.

## References

Padmakumaran Nair KG, Rajamohan T, Kurup PA. (1999). Coconut kernel protein modifies the effect of coconut oil on serum lipids. *Plant Foods Hum Nutr.* 53(2):133-44.

Tighe P, Duthie G, Vaughan N, Brittenden J, Simpson WG, Duthie S, Mutch W, Wahle K, Horgan G, Thies F. (2010). Effect of increased consumption of whole-grain foods on blood pressure and other cardiovascular risk markers in healthy middle-aged persons: a randomized controlled trial. *Am J Clin Nutr.* 92(4), 733-40.

R H Lustig, L A Schmidt, C D Brindis. (2012). Public health: The toxic truth about sugar. *Nature.* 482 27-29.

den Hartog GJ, Boots AW, Adam-Perrot A, Brouns F, Verkooijen IW, Weseler AR, Haenen GR, Bast A. (2010). Erythritol is a sweet antioxidant. *Nutrition.* 26(4), 449-58.

Trumbo PR, Shimakawa T. (2011). Tolerable upper intake levels for trans fat, saturated fat, and cholesterol. *Nutr Rev.* 69(5), 270-8. doi: 10.1111/j.1753-4887.2011.00389.x.

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## See Also

More information about the OpenMx package may be found [here](#).

## Examples

```
# Return a brownie recipe
omxBrownie()
```

---

omxCheckCloseEnough     *Approximate Equality Testing Function*

---

## Description

This function tests whether two numeric vectors or matrixes are approximately equal to one another, within a specified threshold.

## Usage

```
omxCheckCloseEnough(a, b, epsilon = 10-15, na.action = na.fail)
```

## Arguments

a	a numeric vector or matrix
b	a numeric vector or matrix
epsilon	a non-negative tolerance threshold
na.action	either na.fail (default) or na.pass. Use of na.omit or na.exclude is not recommended.

**Details**

Arguments 'a' and 'b' must be of the same type, ie. they must be either vectors of equal dimension or matrices of equal dimension. The two arguments are compared element-wise for approximate equality. If the absolute value of the difference of any two values is greater than the threshold, then an error will be thrown. If 'a' and 'b' are approximately equal to each other, by default the function will print a statement informing the user the test has passed. To turn off these print statements use `options("mxPrintUnitTests" = FALSE)`.

When `na.action` is set to `na.pass`, a and b are expected to have identical missingness patterns.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

[omxCheckWithinPercentError](#), [omxCheckIdentical](#), [omxCheckSetEquals](#), [omxCheckTrue](#), [omxCheckEquals](#)

**Examples**

```
omxCheckCloseEnough(c(1, 2, 3), c(1.1, 1.9, 3.0), epsilon = 0.5)
omxCheckCloseEnough(matrix(3, 3, 3), matrix(4, 3, 3), epsilon = 2)
# Throws an error
try(omxCheckCloseEnough(c(1, 2, 3), c(1.1, 1.9, 3.0), epsilon = 0.01))
```

---

omxCheckEquals

*Equality Testing Function*


---

**Description**

This function tests whether two objects are equal using the '==' operator.

**Usage**

```
omxCheckEquals(a, b)
```

**Arguments**

a                    the first value to compare.  
b                    the second value to compare.

**Details**

Performs the '==' comparison on the two arguments. If the two arguments are not equal, then an error will be thrown. If 'a' and 'b' are equal to each other, by default the function will print a statement informing the user the test has passed. To turn off these print statements use `options("mxPrintUnitTests" = FALSE)`.



**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

[omxCheckCloseEnough](#), [omxCheckWithinPercentError](#), [omxCheckSetEquals](#), [omxCheckTrue](#), [omxCheckIdentical](#)

**Examples**

```
omxCheckEquals(c(1, 2, 3), c(1, 2, 3))  
  
omxCheckEquals(FALSE, FALSE)  
  
# Throws an error  
try(omxCheckEquals(c(1, 2, 3), c(2, 1, 3)))
```

---

omxCheckError	<i>Correct Error Message Function</i>
---------------	---------------------------------------

---

**Description**

This function tests whether the correct error message is thrown.

**Usage**

```
omxCheckError(expression, message)
```

**Arguments**

expression	an R expression that produces an error
message	a character string with the desired error message

**Details**

Arguments 'expression' and 'message' give the expression that generates the error and the message that is supposed to be generated, respectively.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

[omxCheckWarning](#), [omxCheckWithinPercentError](#), [omxCheckIdentical](#), [omxCheckSetEquals](#), [omxCheckTrue](#), [omxCheckEquals](#)

**Examples**

```

A <- mxMatrix('Full', 1, 1, labels = 'data.foo', free = TRUE, name = 'A')
model <- mxModel('model', A)
omxCheckError(mxRun(model),
paste("The definition variable 'data.foo'",
"has been assigned to a",
"free parameter in matrix 'A'"))
omxCheckCloseEnough(matrix(3, 3, 3), matrix(4, 3, 3), epsilon = 2)
# Throws error, check the message
tmsg <- paste("In omxCheckCloseEnough(c(1, 2, 3), c(1.1, 1.9, 3), 0.01)",
": not equal to within 0.01 : '1 2 3' and '1.1 1.9 3'")
omxCheckError(omxCheckCloseEnough(c(1, 2, 3), c(1.1, 1.9, 3.0), .01), tmsg)

```

---

omxCheckIdentical      *Exact Equality Testing Function*

---

**Description**

This function tests whether two objects are equal.

**Usage**

```
omxCheckIdentical(a, b)
```

**Arguments**

a	the first value to compare.
b	the second value to compare.

**Details**

Performs the ‘identical’ comparison on the two arguments. If the two arguments are not equal, then an error will be thrown. If ‘a’ and ‘b’ are equal to each other, by default the function will print a statement informing the user the test has passed. To turn off these print statements use `options("mxPrintUnitTests" = FALSE)`.

**References**

The OpenMx User’s guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

[omxCheckCloseEnough](#), [omxCheckWithinPercentError](#), [omxCheckSetEquals](#), [omxCheckTrue](#), [omxCheckEquals](#)

**Examples**

```

omxCheckIdentical(c(1, 2, 3), c(1, 2, 3))

omxCheckIdentical(FALSE, FALSE)

# Throws an error
try(omxCheckIdentical(c(1, 2, 3), c(2, 1, 3)))

```

---

omxCheckNamespace	<i>omxCheckNamespace</i>
-------------------	--------------------------

---

**Description**

This is an internal function exported for those people who know what they are doing.

**Usage**

```
omxCheckNamespace(model, namespace)
```

**Arguments**

model	model
namespace	namespace

**Details**

This function checks that the named entities in the model are valid.

---

omxCheckSetEquals	<i>Set Equality Testing Function</i>
-------------------	--------------------------------------

---

**Description**

This function tests whether two vectors contain the same elements.

**Usage**

```
omxCheckSetEquals(a, b)
```

**Arguments**

a	the first vector to compare.
b	the second vector to compare.

**Details**

Performs the 'setequal' function on the two arguments. If the two arguments do not contain the same elements, then an error will be thrown. If 'a' and 'b' contain the same elements, by default the function will print a statement informing the user the test has passed. To turn off these print statements use `options("mxPrintUnitTests" = FALSE)`.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

[omxCheckCloseEnough](#), [omxCheckWithinPercentError](#), [omxCheckIdentical](#), [omxCheckTrue](#), [omxCheckEquals](#)

**Examples**

```
omxCheckSetEquals(c(1, 1, 2, 2, 3), c(3, 2, 1))

omxCheckSetEquals(matrix(1, 1, 1), matrix(1, 3, 3))

# Throws an error
try(omxCheckSetEquals(c(1, 2, 3, 4), c(2, 1, 3)))
```

---

omxCheckTrue

*Boolean Equality Testing Function*


---

**Description**

This function tests whether an object is equal to TRUE.

**Usage**

```
omxCheckTrue(a)
```

**Arguments**

a                    the value to test.

**Details**

Checks element-wise whether an object is equal to TRUE. If any of the elements are false, then an error will be thrown. If 'a' is TRUE, by default the function will print a statement informing the user the test has passed. To turn off these print statements use `options("mxPrintUnitTests" = FALSE)`.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

[omxCheckCloseEnough](#), [omxCheckWithinPercentError](#), [omxCheckIdentical](#), [omxCheckSetEquals](#), [omxCheckEquals](#)

**Examples**

```
omxCheckTrue(1 + 1 == 2)

omxCheckTrue(matrix(TRUE, 3, 3))

# Throws an error
try(omxCheckTrue(FALSE))
```

---

omxCheckWarning

*Correct Warning Message Function*

---

**Description**

This function tests whether the correct warning message is thrown.

**Usage**

```
omxCheckWarning(expression, message)
```

**Arguments**

expression	an R expression that produces a warning
message	a character string with the desired warning message

**Details**

Arguments ‘expression’ and ‘message’ give the expression that generates the warning and the message that is supposed to be generated, respectively.

**References**

The OpenMx User’s guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

[omxCheckError](#) [omxCheckWithinPercentError](#), [omxCheckIdentical](#), [omxCheckSetEquals](#), [omxCheckTrue](#), [omxCheckEquals](#)

**Examples**

```

msg <- paste("Objective functions like mxFIMLObjective()",
"have been deprecated in favor of expectation and fit functions.\n",
"Please use mxExpectationNormal(covariance= , means = , ...) instead,",
"and add a call to mxFitFunctionML().",
"See examples at help(mxExpectationNormal)")
foo <- omxCheckWarning(mxFIMLObjective('cov', 'mean'), msg)

```

---

omxCheckWithinPercentError

*Approximate Percent Equality Testing Function*

---

**Description**

This function tests whether two numeric vectors or matrixes are approximately equal to one another, within a specified percentage.

**Usage**

```
omxCheckWithinPercentError(a, b, percent = 0.1)
```

**Arguments**

a	a numeric vector or matrix.
b	a numeric vector or matrix.
percent	a non-negative percentage.

**Details**

Arguments ‘a’ and ‘b’ must be of the same type, ie. they must be either vectors of equal dimension or matrices of equal dimension. The two arguments are compared element-wise for approximate equality. If the absolute value of the difference of any two values is greater than the percentage difference of ‘a’, then an error will be thrown. If ‘a’ and ‘b’ are approximately equal to each other, by default the function will print a statement informing the user the test has passed. To turn off these print statements use `options("mxPrintUnitTests" = FALSE)`.

**References**

The OpenMx User’s guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**See Also**

[omxCheckCloseEnough](#), [omxCheckIdentical](#), [omxCheckSetEquals](#), [omxCheckTrue](#), [omxCheckEquals](#)

## Examples

```
omxCheckWithinPercentError(c(1, 2, 3), c(1.1, 1.9, 3.0), percent = 50)

omxCheckWithinPercentError(matrix(3, 3, 3), matrix(4, 3, 3), percent = 150)

# Throws an error
try(omxCheckWithinPercentError(c(1, 2, 3), c(1.1, 1.9, 3.0), percent = 0.01))
```

---

```
omxConstrainMLThresholds
      omxConstrainMLThresholds
```

---

## Description

Add constraint to ML model to keep thresholds in order

## Usage

```
omxConstrainMLThresholds(model, dist = 0.1)
```

## Arguments

model	the MxModel to which constraints should be added
dist	unused

## Details

This function adds a nonlinear constraint to an ML model. The constraint keeps the thresholds in order. Constraints often slow model estimation, however, keeping the thresholds in increasing order helps ensure the likelihood function is well-defined. If you're having problems with ordinal data, this is one of the things to try.

## Value

a new MxModel object with the constraints added

## See Also

```
demo("omxConstrainMLThresholds")
```

---

omxDefaultComputePlan *Construct default compute plan*

---

### Description

This function generates a default compute plan, where "default compute plan" refers to an object of class [MxComputeSequence](#) which is appropriate for use in a wide variety of cases. The exact specification of the plan will depend upon the arguments provided to `omxDefaultComputePlan()`.

### Usage

```
omxDefaultComputePlan(modelName=NULL, intervals=FALSE,  
  useOptimizer=TRUE, optionList=options())$mxOption)
```

### Arguments

<code>modelName</code>	Optional (defaults to NULL) character string, providing the name of the <a href="#">MxModel</a> the fitfunction of which is to be evaluated, and usually, optimized.
<code>intervals</code>	Logical; will <a href="#">confidence intervals</a> be computed? Defaults to FALSE.
<code>useOptimizer</code>	Logical; will a fitfunction be minimized? Defaults to TRUE.
<code>optionList</code>	List of <a href="#">mxOptions</a> . Defaults to the current list of global <a href="#">mxOptions</a> .

### Details

At minimum, argument `optionList` must include "Gradient algorithm", "Gradient iterations", "Gradient step size", "Calculate Hessian", and "Standard Errors". Users are advised to set "Calculate Hessian" and "Standard Errors" to "No" if the compute plan is to be used in an [MxModel](#) containing [MxConstraints](#).

### Value

Returns an object of class [MxComputeSequence](#).

### Examples

```
foo <- omxDefaultComputePlan(modelName="bar")  
str(foo)
```



---

omxDetectCores	<i>omxDetectCores</i>
----------------	-----------------------

---

**Description**

Detects the number of cores on the local machine

**Usage**

```
omxDetectCores(...)
```

**Arguments**

... unused

---

omxGetBootstrapReplications	<i>omxGetBootstrapReplications</i>
-----------------------------	------------------------------------

---

**Description**

Checks a variety of conditions to ensure that bootstrap replications are available and valid. Throws exception if things go wrong. Otherwise, replications are returned to the caller.

**Usage**

```
omxGetBootstrapReplications(model)  
omxBootstrapCov(model)
```

**Arguments**

model an MxModel object

**Value**

a matrix or covariance matrix of bootstrap parameter estimates

---

omxGetNPSOL

*omxGetNPSOL*


---

**Description**

Get the non-CRAN version of OpenMx from the OpenMx website.

**Usage**

```
omxGetNPSOL()
```

**Details**

This function

**Value**

Invisible NULL

**Examples**

```
## Not run: omxGetNPSOL()
```

---

omxGetParameters

*Fetch Model Parameters*


---

**Description**

Return a vector of the chosen parameters from the model.

**Usage**

```
omxGetParameters(model, indep = FALSE, free = c(TRUE, FALSE, NA),
  fetch = c('values', 'free', 'lbound', 'ubound', 'all'),
  labels = c())
```

**Arguments**

model	a MxModel object
indep	fetch parameters from independent submodels.
free	fetch either free parameters (TRUE), or fixed parameters or both types. Default value is TRUE.
fetch	which attribute of the parameters to fetch. Default choice is 'values'.
labels	additional labels to fetch

## Details

The argument ‘free’ dictates whether to return only free parameters or only fixed parameters or both free and fixed parameters. The function can return unlabelled free parameters (parameters with a label of NA). These anonymous free parameters will be identified as ‘modelname.matrixname[row,col]’. It will not return fixed parameters that have a label of NA.

If provided, the argument ‘labels’ takes precedent over the selection criteria specified by ‘free’. Any labels mentioned in ‘labels’, including those of the form ‘modelname.matrixname[row,col]’, will be returned.

No distinction is made between ordinary labels, definition variables, and square bracket constraints. The function will return either a vector of parameter values, or free/fixed designations, or lower bounds, or upper bounds, depending on the ‘fetch’ argument. Using fetch with ‘all’ returns a data frame that is populated with all of the attributes.

## See Also

[omxSetParameters](#), [omxLocateParameters](#), [omxAssignFirstParameters](#)

## Examples

```
library(OpenMx)

A <- mxMatrix('Full', 2, 2, labels = c("A11", "A12", "A21", NA), values= 1:4,
  free = c(TRUE,TRUE,FALSE,TRUE), byrow=TRUE, name = 'A')
model <- mxModel(A, name = 'model')

# Request all free parameters in model
omxGetParameters(model)

# A11 A12 model.A[2,2]
# 1 2 4

# Request fixed parameters from model
omxGetParameters(model, free = FALSE)
# A21
# 3

A$labels
# [,1] [,2]
# [1,] "A11" "A12"
# [2,] "A21" NA

A$free
# [,1] [,2]
# [1,] TRUE TRUE
# [2,] FALSE TRUE

A$values
# [,1] [,2]
# [1,] 1 2
```

```

# [2,] 3 4

# Example using un-labelled parameters

# Read in some demo data
data(demoOneFactor)
# Grab the names for manifestVars
manifestVars <- names(demoOneFactor)
nVar = length(manifestVars) # 5 variables
factorModel <- mxModel("One Factor",
  mxMatrix(name="A", type="Full", nrow=nVar, ncol=1, values=0.2, free=TRUE,
    lbound = 0.0, labels=letters[1:nVar]),
  mxMatrix(name="L", type="Symm", nrow=1, ncol=1, values=1, free=FALSE),
  # the "U" matrix has nVar (5) anonymous free parameters
  mxMatrix(name="U", type="Diag", nrow=nVar, ncol=nVar, values=1, free=TRUE),
  mxAlgebra(expression=A %% L + U, name="R"),
  mxExpectationNormal(covariance="R", dimnames=manifestVars),
  mxFitFunctionML(),
  mxData(observed=cov(demoOneFactor), type="cov", numObs=500)
)

# Get all free parameters
params <- omxGetParameters(factorModel)
lbound <- omxGetParameters(factorModel, fetch="lbound")
# Set new values for these params, saving them in a new model
newFactorModel <- omxSetParameters(factorModel, names(params), values = 1:10)
# Read out the values from the new model
newParams <- omxGetParameters(newFactorModel)

```

---

omxGetRAMDepth

*omxGetRAMDepth*


---

## Description

Get the potency of a matrix for inversion speed-up

## Usage

```
omxGetRAMDepth(A, maxdepth = nrow(A) - 1)
```

## Arguments

A	MxMatrix object
maxdepth	Numeric. maximum depth to check

**Details**

This function is used internally by the [mxExpectationRAM](#) function to determine how far to expand  $(I - A)^{-1} = I + A + A^2 + A^3 + \dots$ . It is similarly used by [mxExpectationLISREL](#) in expanding  $(I - B)^{-1} = I + B + B^2 + B^3 + \dots$ . In many situations  $A^2$  is a zero matrix (nilpotent of order 2). So when  $A$  has large dimension it is much faster to compute  $I + A$  than  $(I - A)^{-1}$ .

---

omxGraphviz

*Show RAM Model in Graphviz Format*


---

**Description**

The function accepts a RAM style model and outputs a visual representation of the model in Graphviz format. The function will output either to a file or to the console. The recommended file extension for an output file is ".dot".

**Usage**

```
omxGraphviz(model, dotFilename = "")
```

**Arguments**

model	An RAM-type model.
dotFilename	The name of the output file. Use "" to write to console.

**Value**

Invisibly returns a string containing the model description in graphviz format.

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

---

omxHasDefaultComputePlan

*omxHasDefaultComputePlan*


---

**Description**

Determine whether the model has a default complete plan (i.e., not custom).

**Usage**

```
omxHasDefaultComputePlan(model)
```

**Arguments**

model	model
-------	-------

---

omxLapply	<i>On-Demand Parallel Lapply</i>
-----------	----------------------------------

---

**Description**

If the snowfall library is loaded, then this function calls [sflapply](#). Otherwise it invokes [lapply](#).

**Usage**

```
omxLapply(x, fun, ...)
```

**Arguments**

x	a vector (atomic or list) or an expressions vector. Other objects (including classed objects) will be coerced by <a href="#">as.list</a> .
fun	the function to be applied to each element of x.
...	optional arguments to fun.

**See Also**

[omxApply](#), [omxSapply](#)

**Examples**

```
x <- list(a = 1:10, beta = exp(-3:3), logic = c(TRUE,FALSE,FALSE,TRUE))
# compute the list mean for each list element
omxLapply(x,mean)
```

---

omxLocateParameters	<i>Get the location (model, matrix, row, column) and other info for a parameter</i>
---------------------	---

---

**Description**

Returns a data.frame summarizing the *free* parameters in a model, possibly filtered using ‘labels’.

For each located parameter, the label, model, matrix, row, col, value, and lbound & ubound are given as a row in the dataframe.

Duplicated labels return a row for each location in which they are found.

**Usage**

```
omxLocateParameters(model, labels = NULL, indep = FALSE)
```

**Arguments**

model	a MxModel object
labels	optionally specify which free parameters to retrieve.
indep	fetch parameters from independent submodels.

**Details**

Invoking the function with the default value for the 'labels' argument retrieves all the free parameters. The 'labels' argument can be used to select a subset of the free parameters. Note that 'NA' is a valid input to 'labels'.

**See Also**

[omxGetParameters](#), [omxSetParameters](#), [omxAssignFirstParameters](#)

**Examples**

```
A <- mxMatrix('Full', 2, 2, labels = c("A11", "A12", NA, "A11"), values= 1:4,
  free = TRUE, byrow = TRUE, name = 'A')

model <- mxModel(A, name = 'model')

# Request all free parameters in model
omxLocateParameters(model)

# Request free parameters "A11" and all NAs
omxLocateParameters(model, c("A11", NA))

# Works with submodel
B = mxMatrix(name = 'B', 'Full', 1, 2, labels = c("B11", "notme"),
  free = c(TRUE, FALSE), values= pi)
model <- mxModel(model, mxModel(B, name = 'subB'))

# nb: only returns free parameters ('notme' not shown)
omxLocateParameters(model)
```

---

omxLogical

*Logical mxAlgebra() operators*


---

**Description**

omxNot computes the unary negation of the values of a matrix. omxAnd computes the binary and of two matrices. omxOr computes the binary or of two matrices. omxGreaterThan computes a binary greater than of two matrices. omxLessThan computes the binary less than of two matrices. omxApproxEquals computes a binary equals within a specified epsilon of two matrices.

**Usage**

```

omxNot(x)
omxAnd(x, y)
omxOr(x, y)
omxGreaterThan(x, y)
omxLessThan(x, y)
omxApproxEquals(x, y, epsilon)

```

**Arguments**

x	the first argument, the matrix which the logical operation will be applied to.
y	the second argument, applicable to binary functions.
epsilon	the third argument, specifies the error threshold for omxApproxEquals. $\text{Abs}(x[i][j]-y[i][j])$ must be less than $\text{epsilon}[i][j]$ .

**Examples**

```

A <- mxMatrix(values = runif(25), nrow = 5, ncol = 5, name = 'A')
B <- mxMatrix(values = runif(25), nrow = 5, ncol = 5, name = 'B')
EPSILON <- mxMatrix(values = 0.04*1:25, nrow = 5, ncol = 5, name = "EPSILON")

model <- mxModel(A, B, EPSILON, name = 'model')

mxEval(omxNot(A), model)
mxEval(omxGreaterThan(A,B), model)
mxEval(omxLessThan(B,A), model)
mxEval(omxOr(omxNot(A),B), model)
mxEval(omxAnd(omxNot(B), A), model)
mxEval(omxApproxEquals(A,B, EPSILON), model)

```

---

omxManifestModelByParameterJacobian

*Estimate the Jacobian of manifest model with respect to parameters*

---

**Description**

The manifest model excludes any latent variables or processes. For RAM and LISREL models, the manifest model contains only the manifest variables with free means, covariance, and thresholds.

**Usage**

```

omxManifestModelByParameterJacobian(model, defvar.row = 1,
  standardize = FALSE)

```



**Arguments**

model	an mxModel
defvar.row	which row to use for definition variables
standardize	logical, whether or not to standardize the parameters

**Details**

The Jacobian is estimated by the central finite difference.

If the standardize argument is TRUE, then the Jacobian is for the standardized model. For Normal expectations the standardized manifest model has the covariances returned as correlations, the variances returned as ones, the means returned as zeros, and the thresholds are returned as z-scores. For the thresholds the z-scores are computed by using the model-implied means and variances.

**Value**

a matrix with manifests in the rows and original parameters in the columns

**See Also**

[mxGetExpected](#)

---

omxMatrixOperations    *MxMatrix operations*

---

**Description**

omxCbind columnwise binding of two or more MxMatrices. omxRbind rowwise binding of two or more MxMatrices. omxTranspose transpose of MxMatrix.

**Usage**

```
omxCbind(..., allowUnlabeled =
  getOption("mxOptions")["Allow Unlabeled"],
  dimnames = NA, name = NA)
omxRbind(..., allowUnlabeled =
  getOption("mxOptions")["Allow Unlabeled"],
  dimnames = NA, name = NA)
omxTranspose(matrix, allowUnlabeled =
  getOption("mxOptions")["Allow Unlabeled"],
  dimnames = NA, name = NA)
```

**Arguments**

...	two or more MxMatrix objects
matrix	MxMatrix input
allowUnlabeled	whether or not to accept free parameters with NA labels
dimnames	list. The dimnames attribute for the matrix: a list of length 2 giving the row and column names respectively. An empty list is treated as NULL, and a list of length one as row names. The list can be named, and the list names will be used as names for the dimensions.
name	an optional character string indicating the name of the MxMatrix object

---

omxMnor

---

*Multivariate Normal Integration*


---

**Description**

Given a covariance matrix, a means vector, and vectors of lower and upper bounds, returns the multivariate normal integral across the space between bounds.

**Usage**

```
omxMnor(covariance, means, lbound, ubound)
```

**Arguments**

covariance	the covariance matrix describing the multivariate normal distribution.
means	a row vector containing means of the variables of the underlying distribution.
lbound	a row vector containing the lower bounds of the integration in each variable.
ubound	a row vector containing the upper bounds of the integration in each variable.

**Details**

The order of columns in the ‘means’, ‘lbound’, and ‘ubound’ vectors are assumed to be the same as that of the covariance matrix. That is, means[i] is considered to be the mean of the variable whose variance is in covariance[i,i]. That variable will be integrated from lbound[i] to ubound[i] as part of the integration.

The value of ubound[i] or lbound[i] may be set to Inf or -Inf if a boundary at positive or negative infinity is desired.

For all i, ubound[i] must be strictly greater than lbound[i].

**Examples**

```

data(myFADataRaw)

covariance <- cov(myFADataRaw[,1:3])
means <- colMeans(myFADataRaw[,1:3])
lbound <- c(-Inf, 0, 1) # Integrate from -Infinity to 0 on first variable
ubound <- c(0, Inf, 2.5) # From 0 to +Infinity on second, and from 1 to 2.5 on third
omxMnor(covariance, means, lbound, ubound)
# 0.0005995

# An alternative specification of the bounds follows
# Integrate from -Infinity to 0 on first variable
v1bound = c(-Inf, 0)
# From 0 to +Infinity on second
v2bound = c(0, Inf)
# and from 1 to 2.5 on third
v3bound = c(1, 2.5)
bounds <- cbind(v1bound, v2bound, v3bound)
lbound <- bounds[1,]
ubound <- bounds[2,]
omxMnor(covariance, means, lbound, ubound)

```

---

omxModelDeleteData	<i>Remove all instances of data from a model</i>
--------------------	--

---

**Description**

For very large data, it can be desirable to discard data after the model is run. That is what the purpose of this function.

Data is discarded from the model and all submodels recursively.

**Usage**

```
omxModelDeleteData(model)
```

**Arguments**

model            a MxModel object.

**Examples**

```

library(OpenMx)

data(demoOneFactor)
manifests <- names(demoOneFactor)
latents <- c("G")

```

```

factorModel <- mxModel(model="One Factor", type="RAM",
  manifestVars = manifests,
  latentVars   = latents,
  mxPath(from=latents, to=manifests),
  mxPath(from=manifests, arrows=2),
  mxPath(from=latents, arrows=2, free=FALSE, values=1.0),
  mxData(cov(demoOneFactor), type="cov", numObs=500)
)
factorFit <- mxRun(factorModel)
object.size(factorFit)
factorFit <- omxModelDeleteData(factorFit)
object.size(factorFit)
factorFit$data

```

---

```

omxNameAnonymousParameters
      omxNameAnonymousParameters

```

---

### Description

Assign new names to the unnamed parameters

### Usage

```
omxNameAnonymousParameters(model, indep = FALSE)
```

### Arguments

model	the MxModel
indep	whether models are independent

### Value

a list with components for the new MxModel with named parameters, and the new names.

---

```

omxParallelCI      Calculate confidence intervals without re-doing the primary optimization.

```

---

### Description

OpenMx provides two functions to calculate confidence intervals for already-run **MxModel** objects that contain an **MxInterval** object (i.e., an **mxCI()** statement), without recalculating point estimates, fitfunction derivatives, or expectations.

The primary function is **omxRunCI()**. This is a wrapper for **omxParallelCI()** with arguments **run=TRUE** and **independentSubmodels=FALSE**, and is the recommended interface.

**omxParallelCI()** does the work of calculating confidence intervals. The "parallel" in the function's name refers to the not-yet-implemented feature of running independent **submodels** in parallel.

**Usage**

```
omxRunCI(model, verbose = 0, optimizer = "SLSQP")
```

```
omxParallelCI(model, run = TRUE, verbose = 0, independentSubmodels = TRUE,
optimizer = mxOption(NULL, "Default optimizer"))
```

**Arguments**

model	An <a href="#">MxModel</a> object that contains an <a href="#">MxInterval</a> object (i.e., an <a href="#">mxCI()</a> statement).
run	Logical; For <a href="#">omxParallelCI()</a> , determines if the model with its new compute plan is <a href="#">mxRun()</a> before being returned. Hard-coded TRUE for <a href="#">omxRunCI()</a> .
verbose	Integer; defaults to zero; verbosity level passed to <a href="#">MxCompute*</a> objects.
independentSubmodels	Logical; For <a href="#">omxParallelCI()</a> defaults to TRUE. Hard coded FALSE for <a href="#">omxRunCI()</a> . Also see "Details."
optimizer	Character string selecting the gradient-descent optimizer to be used to find confidence limits; one of "NPSOL", "CSOLNP", or "SLSQP". The default for <a href="#">omxParallelCI()</a> is the current value of <a href="#">mxOption</a> "Default optimizer", and for <a href="#">omxRunCI()</a> , is "SLSQP".

**Details**

When `independentSubmodels=TRUE`, [omxParallelCI\(\)](#) creates an independent [MxModel](#) object for each quantity specified in the 'reference' slot of model's [MxInterval](#) object, and places these independent [MxModels](#) inside model. Each of these independent submodels calculates the confidence limits of its own quantity when the container model is run. When `independentSubmodels=FALSE`, no submodels are added to model. Instead, model is provided with a dedicated [compute plan](#) consisting only of an [MxComputeConfidenceInterval](#) step. Note that using `independentSubmodels=FALSE` will overwrite any compute plan already inside model.

**Value**

The functions return model, augmented with independent submodels (if `independentSubmodels=TRUE`) or with a non-default compute plan (if `independentSubmodels=FALSE`), and possibly having been passed through [mxRun\(\)](#) (if `run=TRUE`). Naturally, if `run=FALSE`, the user can subsequently [run](#) the returned model to obtain confidence intervals. Users are cautioned that the returned model may not be very amenable to being further modified and re-fitted (e.g., having some free parameters fixed via [omxSetParameters\(\)](#) and passed through [mxRun\(\)](#) to get new point estimates) unless the added submodels or the non-default compute plan are eliminated. The exception is if `run=TRUE` and `independentSubmodels=TRUE` (which is always the case with [omxRunCI\(\)](#)), since the non-default compute plan is set to be non-persistent, and will automatically be replaced with a default compute plan the next time the model is passed to [mxRun\(\)](#).

**See Also**

[mxCI\(\)](#), [MxInterval](#), [mxComputeConfidenceInterval\(\)](#)

**Examples**

```

require(OpenMx)
# 1. Build and run a model, don't compute intervals yet
data(demoOneFactor)
manifests <- names(demoOneFactor)
latents <- c("G")
factorModel <- mxModel("One Factor", type="RAM",
  manifestVars=manifests,
  latentVars=latents,
  mxPath(from=latents, to=manifests),
  mxPath(from=manifests, arrows=2),
  mxPath(from=latents, arrows=2, free=FALSE, values=1.0),
  mxData(observed=cov(demoOneFactor), type="cov", numObs=500),
  # Add confidence intervals for (free) params in A and S matrices.
  mxCI(c('A', 'S'))
)
factorRun <- mxRun(factorModel)

# 2. Compute the CIs on factorRun, and view summary
factorCI1 <- omxRunCI(factorRun)
summary(factorCI1)$CI

# 3. Use low-level omxParallelCI interface
factorCI2 <- omxParallelCI(factorRun)

# 4. Build, but don't run the newly-created model
factorCI3 <- omxParallelCI(factorRun, run= FALSE)

```

---

omxQuotes

*omxQuotes*


---

**Description**

Quote helper function, often for error messages.

**Usage**

```
omxQuotes(name)
```

**Arguments**

name                    a character vector

**Details**

This is a helper function for creating a nicely put together formatted string.

**Value**

a character string

**Examples**

```
omxQuotes(c("Oh", "blah", "dee", "Oh", "blah", "da"))
omxQuotes(c("A", "S", "F"))
omxQuotes("Hello World")
```

---

omxRAMtoML

*omxRAMtoML*


---

**Description**

Convert a RAM model to an ML model

**Usage**

```
omxRAMtoML(model)
```

**Arguments**

model            the MxModel

**Details**

This is a legacy function that was once used to convert RAM models to ML models in the old (1.0 release of OpenMx) objective function style.

**Value**

an ML model with an ML objective

---

omxRMSEA

*Get the RMSEA with confidence intervals from model*


---

**Description**

This function calculates the Root Mean Square Error of the Approximation (RMSEA) for a model and computes confidence intervals for that fit statistic.

**Usage**

```
omxRMSEA(model, lower=.025, upper=.975, null=.05, ...)
```

**Arguments**

model	An MxModel object for which the RMSEA is desired
lower	The lower confidence bound for the confidence interval
upper	The upper confidence bound for the confidence interval
null	Value of RMSEA used to test for close fit
...	Further named arguments passed to summary

**Details**

To help users obtain fit statistics related to the RMSEA, this function confidence intervals and a test for close fit. The user determines how close the fit is required to be by setting the null argument to the value desired for comparison.

**Value**

A named vector with elements lower, est.rmsea, upper, null, and 'Prob(x <= null)'.

**References**

Browne, M. W. & Cudeck, R. (1992). Alternative Ways of Assessing Model Fit. *Sociological Methods and Research*, 21, 230-258.

**Examples**

```
require(OpenMx)
data(demoOneFactor)
manifests <- names(demoOneFactor)
latents <- c("G")
factorModel <- mxModel("One Factor",
                        type="RAM",
                        manifestVars=manifests,
                        latentVars=latents,
                        mxPath(from=latents, to=manifests),
                        mxPath(from=manifests, arrows=2),
                        mxPath(from=latents, arrows=2, free=FALSE, values=1.0),
                        mxData(observed=cov(demoOneFactor), type="cov", numObs=500))
factorRun <- mxRun(factorModel)
factorSat <- mxRefModels(factorRun, run=TRUE)
summary(factorRun, refModels=factorSat)
# Gives RMSEA with 95% confidence interval

omxRMSEA(factorRun, .05, .95, refModels=factorSat)
# Gives RMSEA with 90% confidence interval
# and probability of 'close enough' fit
```



---

omxSapply	<i>On-Demand Parallel Sapply</i>
-----------	----------------------------------

---

**Description**

If the snowfall library is loaded, then this function calls [sfSapply](#). Otherwise it invokes [sapply](#).

**Usage**

```
omxSapply(x, fun, ..., simplify = TRUE, USE.NAMES = TRUE)
```

**Arguments**

x	a vector (atomic or list) or an expressions vector. Other objects (including classed objects) will be coerced by <a href="#">as.list</a> .
fun	the function to be applied to each element of x.
...	optional arguments to fun.
simplify	logical; should the result be simplified to a vector or matrix if possible?
USE.NAMES	logical; if TRUE and if x is a character, use x as <a href="#">names</a> for the result unless it had names already.

**See Also**

[omxApply](#), [omxLapply](#)

**Examples**

```
x <- list(a = 1:10, beta = exp(-3:3), logic = c(TRUE,FALSE,FALSE,TRUE))
# compute the list mean for each list element
omxSapply(x, quantile)
```

---

omxSaturatedModel	<i>Create Reference (Saturated and Independence) Models</i>
-------------------	---

---

**Description**

This function creates and, optionally, runs saturated and independence (null) models of a base model or data set for use with [mxSummary](#) to enable fit indices that depend on these models.

**Usage**

```
mxRefModels(x, run=FALSE, ..., distribution="default")
```

**Arguments**

x	A MxModel object, data frame, or matrix.
run	logical. If TRUE, runs the models before returning; otherwise returns built models without running.
...	Not used. Forces remaining arguments to be specified by name.
distribution	character. Which distribution to assume.

**Details**

For typical structural equation models the saturated model is the free-est possible model. Not only all variances (and, when possible, all means) are estimated, but also all covariances. In the case of ordinal data, the ordinal means are fixed to zero and the thresholds are estimated. For binary variables, those variances are also constrained to one. This is the free-est possible model that is identified. The saturated model is used in calculating fit statistics such as the RMSEA, and Chi-squared fit indices.

The independence model, sometimes called the null model, is a model in which each variable is treated as being completely independent of every other variable. As such, all the variances and, when possible, all means are estimated. However, covariances are set to zero. Ordinal variables are handled the same for the independence and saturated models. The independence model is used, along with the saturated model, to create CFI and TLI fit indices.

The saturated and independence models could be used to create further fit indices. However, OpenMx does not recommend using GFI, AGFI, NFI (aka Bentler-Bonett), or SRMR. The page for [mxSummary](#) has information about why.

When the [mxFitFunctionMultigroup](#) fit function is used, `mxRefModels` creates the appropriate multi-group saturated and independence models. Saturated and independence models are created separately for each group. Each group has its own saturated and independence model. The multi-group saturated model is a multi-group model where each group has its own saturated model, and similarly for the independence model.

One potentially important limitation of the `mxRefModels` function is for behavior-genetic models. If variables 'x', 'y', and 'z' are measured on twins 1 and 2 creating the modeled variables 'x1', 'y1', 'z1', 'x2', 'y2', 'z2', then this function may not create the intended saturated or independence models. In particular, the means of 'x1' and 'x2' are estimated separately. Similarly, the covariance of 'x1' with 'y1' and 'x2' with 'y2' are allowed to be distinct:  $cov(x1, y1) \neq cov(x2, y2)$ . Moreover, the cross-twin covariances are estimated: e.g.  $cov(x1, y2) \neq 0$ .

Another potential misuse of this function is for models with definition variables. If definition variables are used, the saturated and independence model may not be correct because they do not account for the definition variables.

When an MxModel has been run, some effort is made to make the reference models for only the variables used in the model. For covariance data, all variables are modeled by default. For raw data when the model has been run, only the modeled variables are used in the reference models. This matches the behavior of [mxModel](#).

In general, it is best practice to give `mxRefModels` a model that has already been run.

There are a few considerations specific to IFA models ([mxExpectationBA81](#)). The independence model preserves equality constraints among item parameters from the original model. The saturated model is a multinomial distribution with the proportions equal to the proportions in your data. For

example, if you have 2 dichotomous items then there are 4 possible response patterns: 00, 01, 10, 11. A multinomial distribution for these 2 items is fully specified by 3 proportions or 3 parameters:  $a, b, c, 1.0 - (a + b + c)$ . Hence, there is no need to optimize the saturated model. When there is no missing data, the deviance is immediately known as  $-2 * \text{sum}(\log\text{proportions})$ . Typical Bayesian priors involve latent factors (various densities on the pseudo-guessing lower bound, log norm on loading, and uniqueness prior). These priors cannot be included in the independence model because there are no latent factors. Therefore, exercise caution when comparing the independence model to a model that includes Bayesian priors.

Multivariate normal models with all ordinal data and no missing values can use the saturated multinomial distribution. This is much faster than estimation of the saturated multivariate normal model. Use `distribution='multinomial'` to avail this option.

`mxRefModels()` is not compatible with [GREML expectation](#), as there is no sensible general definition for a saturated GREML-type model.

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

## Examples

```
require(OpenMx)
data(demoOneFactor)
manifests <- names(demoOneFactor)
latents <- c("G")
factorModel <- mxModel("OneFactor", type = "RAM",
  manifestVars = manifests, latentVars = latents,
  mxPath(from = latents, to=manifests, values = diag(var(demoOneFactor))*2),
  mxPath(from = manifests, arrows = 2, values = diag(var(demoOneFactor))*8),
  mxPath(from = latents, arrows = 2, free = FALSE, values = 1),
  mxData(cov(demoOneFactor), type = "cov", numObs = 500)
)
factorRun <- mxRun(factorModel)
factorSat <- mxRefModels(factorRun, run=TRUE)
summary(factorRun)
summary(factorRun, refModels=factorSat)

# A raw-data example where using mxRefModels adds fit indices
## Not run:
m1 <- mxModel("OneFactor", type = "RAM",
  manifestVars = manifests, latentVars = latents,
  mxPath(latents, to=manifests, values = diag(var(demoOneFactor))*2),
  mxPath(manifests, arrows = 2, values = diag(var(demoOneFactor))*8),
  mxPath(latents, arrows = 2, free = FALSE, values = 1),
  mxPath("one", to = latents, free = FALSE, values = 0),
  mxPath("one", to = manifests, values = 0),
  mxData(demoOneFactor, type = "raw")
)
m1 <- mxRun(m1)
summary(m1) # CFI, TLI, RMSEA missing
summary(m1, refModels=mxRefModels(m1, run = TRUE))
```

```
## End(Not run)
```

---

omxSelectRowsAndCols *Filter rows and columns from an mxMatrix*

---

### Description

This function filters rows and columns from a matrix using a single row or column R matrix as a selector.

### Usage

```
omxSelectRowsAndCols(x, selector)
omxSelectRows(x, selector)
omxSelectCols(x, selector)
```

### Arguments

x	the matrix to be filtered
selector	A single row or single column R matrix indicating which values should be filtered from the mxMatrix.

### Details

omxSelectRowsAndCols, omxSelectRows, and omxSelectCols returns the filtered entries in a target matrix specified by a single row or single column selector matrix. Each entry in the selector matrix is treated as a logical data indicating if the corresponding entry in the target matrix should be excluded (0 or FALSE) or included (not 0 or TRUE). Typically the function is used to filter data from a target matrix using an existence vector which specifies what data entries are missing. This can be seen in the demo: RowObjectiveFIMLBivariateSaturated.

### Value

Returns a new matrix with the filtered data.

### References

The function is most often used when filtering data for missingness. This can be seen in the demo: RowObjectiveFIMLBivariateSaturated. The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>. The omxSelect\* functions share some similarity to the Extract function in the R programming language.

**Examples**

```

loadings <- c(1, -0.625, 0.1953125, 1, -0.375, 0.0703125, 1, -0.375, 0.0703125)
loadings <- matrix(loadings, 3, 3, byrow= TRUE)
existenceList <- c(1, 0, 1)
existenceList <- matrix(existenceList, 1, 3, byrow= TRUE)
rowsAndCols <- omxSelectRowsAndCols(loadings, existenceList)
rows <- omxSelectRows(loadings, existenceList)
cols <- omxSelectCols(loadings, existenceList)

```

---

omxSetParameters      *Assign Model Parameters*

---

**Description**

Modify the attributes of parameters in a model. This function cannot modify parameters that have NA labels. Often you will want to call [omxAssignFirstParameters](#) after using this, to force the starting values of equated parameters to the same value (otherwise the model cannot begin to be evaluated)

**Usage**

```

omxSetParameters(model, labels, free = NULL, values = NULL,
  newlabels = NULL, lbound = NULL, ubound = NULL, indep = FALSE,
  strict = TRUE, name = NULL)

```

**Arguments**

model	an MxModel object.
labels	a character vector of target parameter names.
free	a boolean vector of parameter free/fixed designations.
values	a numeric vector of parameter values.
newlabels	a character vector of new parameter names.
lbound	a numeric vector of lower bound values.
ubound	a numeric vector of upper bound values.
indep	boolean. set parameters in independent submodels.
strict	boolean. If TRUE then throw an error when a label does not appear in the model.
name	character string. (optional) a new name for the model.

**See Also**

[omxGetParameters](#), [omxAssignFirstParameters](#)

## Examples

```
A <- mxMatrix('Full', 3, 3, labels = c('a','b', NA), free = TRUE, name = 'A')
model <- mxModel(model="testModel", A, name = 'model')

# set value of cells labelled "a" and "b" to 1 and 2 respectively
model <- omxSetParameters(model, c('a', 'b'), values = c(1, 2))

# set label of cell labelled "a" to "b" and vice versa
model <- omxSetParameters(model, c('a', 'b'), newlabels = c('b', 'a'))

# set label of cells labelled "a" to "b"
model <- omxSetParameters(model, c('a'), newlabels = 'b')

# ensure initial values are the same for each instance of a labeled parameter
model <- omxAssignFirstParameters(model)
```

---

omxSymbolTable	<i>Internal OpenMx algebra operations</i>
----------------	---

---

## Description

This is an internal table used in the OpenMx backend.

---

OpenMx	<i>OpenMx: An package for Structural Equation Modeling and Matrix Algebra Optimization</i>
--------	--

---

## Description

OpenMx is a package for structural equation modeling, matrix algebra optimization and other statistical estimation problems. Try the example below. We try and have useful help files: for instance `help(mxRun)` to learn more. Also the reference manual

## Details

OpenMx solves algebra optimization and statistical estimation problems using matrix algebra. Most users use it for Structural equation modeling.

The core function is `mxModel`, which makes a model. Models are containers for data, matrices, `mxPaths` algebras, bounds and constraints. Models most often have an expectation function (e.g., `mxExpectationNormal`) to calculate the expectations for the model. Models need a fit function. Several of these are built-in (e.g., `mxFitFunctionML`) OpenMx also allows user-defined fit functions for purposes not covered by the built-in functions. (e.g., `mxFitFunctionR` or `mxFitFunctionAlgebra`).

Once built, the resulting `mxModel` can be run (i.e., optimized) using `mxRun`. This returns the fitted model.

You can see the resulting parameter estimates, algebra evaluation etc using `summary(yourModel)`

The user's manual is online (see reference below), but functions `mxRun`, `mxModel`, `mxMatrix` all have working examples to get you started as well.

The main OpenMx functions are: `mxAlgebra`, `mxBounds`, `mxCI`, `mxConstraint`, `mxData`, `mxMatrix`, `mxModel`, and `mxPath`

Expectation functions include `mxExpectationNormal`, `mxExpectationRAM`, `mxExpectationLISREL`, and `mxExpectationStateSpace`;

Fit functions include `mxFitFunctionML`, `mxFitFunctionAlgebra`, `mxFitFunctionRow` and `mxFitFunctionR`.

OpenMx comes with several useful datasets built-in. Access them using `data(package="OpenMx")`

To cite package 'OpenMx' in publications use:

Michael C. Neale, Michael D. Hunter, Joshua N. Pritikin, Mahsa Zahery, Timothy R. Brick Robert M. Kirkpatrick, Ryne Estabrook, Timothy C. Bates, Hermine H. Maes, Steven M. Boker. (in press). OpenMx 2.0: Extended structural equation and statistical modeling. *Psychometrika*. DOI: 10.1007/s11336-014-9435-8

Steven M. Boker, Michael C. Neale, Hermine H. Maes, Michael J. Wilde, Michael Spiegel, Timothy R. Brick, Jeffrey Spies, Ryne Estabrook, Sarah Kenny, Timothy C. Bates, Paras Mehta, and John Fox. (2011) OpenMx: An Open Source Extended Structural Equation Modeling Framework. *Psychometrika*, 306-317. DOI:10.1007/s11336-010-9200-6

Steven M. Boker, Michael C. Neale, Hermine H. Maes, Michael J. Wilde, Michael Spiegel, Timothy R. Brick, Ryne Estabrook, Timothy C. Bates, Paras Mehta, Timo von Oertzen, Ross J. Gore, Michael D. Hunter, Daniel C. Hackett, Julian Karch, Andreas M. Brandmaier, Joshua N. Pritikin, Mahsa Zahery, Robert M. Kirkpatrick, Yang Wang, and Charles Driver. (2016) OpenMx 2 User Guide. <http://openmx.ssri.psu.edu/docs/OpenMx/latest/OpenMxUserGuide.pdf>

## References

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>

## Examples

```
library(OpenMx)
data(demoOneFactor)
# =====
# = Make and run a 1-factor CFA =
# =====

latents = c("G") # the latent factor
manifests = names(demoOneFactor) # manifest variables to be modeled
# =====
# = Make the MxModel =
# =====
m1 <- mxModel("One Factor", type = "RAM",
manifestVars = manifests, latentVars = latents,
mxPath(from = latents, to = manifests),
mxPath(from = manifests, arrows = 2),
mxPath(from = latents, arrows = 2, free = FALSE, values = 1.0),
```

```
mxData(cov(demoOneFactor), type = "cov", numObs = 500)
)

# =====
# = mxRun it and get a summary! =
# =====

m1 = mxRun(m1)
summary(m1)
```

---

ordinalTwinData

*Data for ordinal twin model*

---

### Description

Example data for ordinal twin-data modelling. Three variables measured in each twin.

### Usage

```
data("ordinalTwinData")
```

### Format

A data frame with 139 observations on the following 7 variables.

zyg a numeric vector  
var1\_twin1 a numeric vector  
var2\_twin1 a numeric vector  
var3\_twin1 a numeric vector  
var1\_twin2 a numeric vector  
var2\_twin2 a numeric vector  
var3\_twin2 a numeric vector

### Examples

```
data(ordinalTwinData)
str(ordinalTwinData)
```



---

rvectorize	<i>Vectorize By Row</i>
------------	-------------------------

---

### Description

This function returns the vectorization of an input matrix in a row by row traversal of the matrix. The output is returned as a column vector.

### Usage

```
rvectorize(x)
```

### Arguments

x                    an input matrix.

### See Also

[cvectorize](#), [vech](#), [vechs](#)

### Examples

```
rvectorize(matrix(1:9, 3, 3))  
rvectorize(matrix(1:12, 3, 4))
```

---

summary.MxModel	<i>Model Summary</i>
-----------------	----------------------

---

### Description

This function returns summary statistics of a model. These include model statistics (parameters, degrees of freedom and likelihood), fit statistics such as AIC, parameter estimates and standard errors (when available), as well as version and timing information and possible warnings about estimates.

### Usage

```
## S3 method for class 'MxModel'  
summary(object, ..., verbose=FALSE)
```

**Arguments**

object	A MxModel object.
...	Any number of named arguments (see below).
verbose	Whether to include extra diagnostic information.

**Details**

mxSummary allows the user to set or override the following parameters of the model:

**numObs** Numeric. Specify the total number of observations for the model.

**numStats** Numeric. Specify the total number of observed statistics for the model.

**refModels** List of MxModel objects. Specify a saturated and independence likelihoods in single argument for testing.

**SaturatedLikelihood** Numeric or MxModel object. Specify a saturated likelihood for testing.

**SaturatedDoF** Numeric. Specify the degrees of freedom of the saturated likelihood for testing.

**IndependenceLikelihood** Numeric or MxModel object. Specify an independence likelihood for testing.

**IndependenceDoF** Numeric. Specify the degrees of freedom of the independence likelihood for testing.

**indep** Logical. Set to FALSE to ignore independent submodels in summary.

**verbose** logical. Changes the printing style for summary (see Details)

**boot.quantile** numeric. A vector of quantiles to be used to summarize bootstrap replication.

**boot.SummaryType** character. One of 'quantile' or 'bcpci'.

**Standard Output**

The standard output consists of a table of free parameters, tables of model and fit statistics, information on the time taken to run the model, the optimizer used, and the version of OpenMx.

**Table of free parameters**

Free parameters in the model are reported in a table with columns for the name (label) of the parameter, the matrix, row and col containing the parameter, the parameter estimate itself, and any lower or upper bounds set for the parameter.

*note:* An exclamation mark ("!") printed after a bound in the lbound or ubound columns indicates that the solution was sufficiently close to the bound that the optimizer could not ignore the bound during its last few iterations.

**Additional columns: standard errors and 'A' (asymmetry) warning column**

When the information matrix is available, either approximated by the Hessian or from bootstrap resampling, standard errors are reported in the column "Std.Error".

If the information matrix was estimated using finite differences then an additional diagnostic column 'A' is displayed. An exclamation point in the 'A' column indicates that the gradient appears to be asymmetric and the standard error may not accurately reflect the variability of that parameter. As a precaution, it is recommended that you compare the SEs with likelihood-based or bootstrap confidence intervals.

### Fit statistics

AIC and BIC Information Criteria are reported in a table showing different versions of the information criteria obtained using different penalties. AIC is reported with both a Parameters Penalty and a Degrees of Freedom Penalty version. AIC generally takes the form  $Fit + 2 * k$ . With the Parameters Penalty version,  $k$  is the number of free parameters:  $AIC.param = Fit + 2 * param$ . With the Degrees of Freedom Penalty,  $k$  is minus one times the model degrees of freedom. So the penalty is subtracted instead of added:  $AIC.param = Fit - 2 * df$ . The Degrees of Freedom penalty was used in Classic Mx. BIC is defined similarly:  $Fit + k * log(N)$  where  $k$  is either the number of free parameters or minus one times the model degrees of freedom. The Sample-Size-Adjusted BIC is only defined for the parameters penalty:  $Fit + k * log((N + 2)/24)$ . Similarly, the Sample-Size-Adjusted AIC is  $Fit + 2 * k + 2 * k * (k + 1) / (N - k - 1)$ . For raw data models,  $Fit$  is the minus 2 log likelihood,  $-2LL$ . For covariance data,  $Fit$  is the Chi-squared statistic. The  $-2LL$  and saturated likelihood values reported under covariance data are not necessarily meaningful on their own, but their difference yields the Chi-squared value.

### Additional fit statistics

When the model has a saturated likelihood, several additional fit indices are printed, including Chi-Squared, CFI, TLI, RMSEA and p RMSEA  $\leq 0.05$ . For covariance data, saturated and independence models are fitted automatically so all fit indices are reported.

For raw data (to save computational time), the reference models needed to compute these absolute statistics are **not estimated** by default. They are available once you fit reference models.

The `refModels`, `SaturatedLikelihood`, `SaturatedDoF`, `IndependenceLikelihood`, and `IndependenceDoF` arguments can be used to obtain these additional fit statistics. An easy way to make reference models for most cases is provided by the `mxRefModels` function (see the example given in `mxRefModels`).

When the `SaturatedLikelihood` or `IndependenceLikelihood` arguments are used, OpenMx attempts to calculate the appropriate degrees of freedom. However, depending on the model, it may sometimes be necessary for the user to also explicitly provide the corresponding `SaturatedDoF` and/or `IndependenceDoF`. Again, for the vast majority of cases, the `mxRefModels` function handles these situations effectively and conveniently.

### Notes on fit statistics

With regard to RMSEA, it is important to note that OpenMx does not currently make a multigroup adjustment that some other structural equation modeling programs make. In particular, we do not multiply the single-group RMSEA by the square root of the number of groups as suggested by Steiger (1998). The RMSEA we use is based on the model likelihood (and degrees of freedom) as compared to the saturated model likelihood (and degrees of freedom), and we do not feel the adjustment is appropriate in this case.

OpenMx does not recommend (and does not compute) some fit indices including GFI, AGFI, NFI, and SRMR. The Goodness of Fit Index (GFI) and Adjusted Goodness of Fit Index (AGFI) are not recommended because they are strongly influenced by sample size and have rather high Type I error rates (Sharma, Mukherjee, Kumar, & Dillon, 2005). The Normed Fit Index (NFI) has no penalty for model complexity. That is, adding more parameters to a model always improves the NFI, regardless of how useful those parameters are. Because the Non-Normed Fit Index (NNFI), also known as the Tucker-Lewis Index (TLI), does adjust for model complexity it is used instead. Lastly, the Standardized Root Mean Square Residual (SRMR) is not reported because it (1) only applies to covariance models, having no direct extension to missing data, (2) has no penalty for model complexity, similar to the NFI, and (3) is positively biased (Hu & Bentler, 1999).

**verbose**

The verbose argument changes the printing style for the summary of a model. When verbose=FALSE, a relatively minimal amount of information is printed: the free parameters, the likelihood, and a few fit indices. When verbose=TRUE, the compute plan, data summary, and additional timing information are always printed. Moreover, available fit indices are printed regardless of whether or not they are defined. The undefined fit indices are printed as NA. In addition, the condition number of the information matrix, and the maximum absolute gradient may also be shown.

*note:* The verbose argument only changes the printing style, all of the same information is calculated and exists in the output of summary. More information is displayed when verbose=TRUE, and less when verbose=FALSE.

**Summary for bootstrap replications**

Summarization of bootstrap replications is controlled by two options: 'boot.quantile' and 'boot.SummaryType'. To obtain a two-sided 95% width confidence interval, use boot.quantile=c(.025, .975). Options for 'boot.SummaryType' are 'quantile' (using R's standard stats:quantile function) and 'bcpci' for bias-corrected bootstrap confidence intervals. The latter, 'bcpci', is the default due to its superior theoretical properties.

**References**

- The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.
- Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, 6, 1-55.
- Savalei, V. (2012). The relationship between root mean square error of approximation and model misspecification in confirmatory factor analysis models. *Educational and Psychological Measurement*, 72(6), 910-932.
- Sharma, S., Mukherjee, S., Kumar, A., & Dillon, W.R. (2005). A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models. *Journal of Business Research*, 58, 935-43.
- Steiger, J. H. (1998). A note on multiple sample extensions of the RMSEA fit index. *Structural Equation Modeling: A Multidisciplinary Journal*, 5(4), 411-419. DOI: 10.1080/10705519809540115

**See Also**

[mxBootstrap mxCI as.statusCode](#)

**Examples**

```
library(OpenMx)
data(demoOneFactor) # load the demoOneFactor dataframe
manifests <- names(demoOneFactor) # set the manifest to the 5 demo variables
latents <- c("G") # define 1 latent variable
model <- mxModel(model="One Factor", type="RAM",
  manifestVars = manifests,
  latentVars = latents,
  mxPath(from = latents, to=manifests, labels = paste("b", 1:5, sep = "")),
  mxPath(from = manifests, arrows = 2, labels = paste("u", 1:5, sep = "")),
```

```

    mxPath(from = latents, arrows = 2, free = FALSE, values = 1.0),
    mxData(cov(demoOneFactor), type = "cov", numObs = 500)
)
model <- mxRun(model) # Run the model, returning the result into model

# Show summary of the fitted model
summary(model)

# Compute the summary and store in the variable "statistics"
statistics <- summary(model)

# Access components of the summary
statistics$parameters
statistics$SaturatedLikelihood

# Specify a saturated likelihood for testing
summary(model, SaturatedLikelihood = -3000)

# Add a CI and view it in the summary
model = mxRun(mxModel(model=model, mxCI("b5")), intervals = TRUE)
summary(model)

```

---

tr

*trace*


---

## Description

This function returns the trace of an n-by-n square matrix  $x$ , defined to be the sum of the elements on the main diagonal (the diagonal from the upper left to the lower right).

## Usage

```
tr(x)
```

## Arguments

$x$  an input matrix. Must be square

## Details

The input matrix must be square.

## See Also

[vech](#), [rvectorize](#), [cvectorize](#)

**Examples**

```
tr(matrix(1:9, 3, 3))
tr(matrix(1:12, 3, 4))
```

---

twinData

*Australian twin sample biometric data.*


---

**Description**

Australian twin data with 3,808 observations on the 12 variables including body mass index (BMI) assessed in both MZ and DZ twins.

Questionnaires were mailed to 5,967 pairs age 18 years and over. These data consist of completed questionnaires returned by both members of 3,808 (64 percent) pairs. There are two cohort blocks in the data: a younger group (zyg 1:5), and an older group (zyg 6:10)

It is a wide dataset, with two individuals per line. Families are identified by the variable “fam”.

Data include zygosity (zyg), along with heights in metres, weights in kg, and the derived variables BMI in kg/m<sup>2</sup> (stored as “htwt1” and “htwt2”), as well as the 7 times the natural log of this variable, stored as bmi1 and bmi2. The logged values are more closely normally distributed while scaling by 7 places them into a similar range to the original variable.

For convenience, zyg is broken out into separate “zygosity” and “cohort” factors. “zygosity” is coded as a factor with 5-levels: MZFF, MZMM, DZFF, DZMM, DZOS. DZOS are in Female/Male wide order.

**Usage**

```
data(twinData)
```

**Format**

A data frame with 3808 observations on the following 12 variables.

fam The family ID  
age Age in years (of both twins)  
zyg Code for zygosity and cohort (see details)  
part A numeric vector  
wt1 Weight of twin 1 (kg)  
wt2 Weight of twin 2 (kg)  
ht1 Height of twin 1 (m)  
ht2 Height of twin 2 (m)  
htwt1 Raw BMI of twin 1 (kg/m<sup>2</sup>)

htwt2 Raw BMI of twin 2 (kg/m<sup>2</sup>)

bmi1 7\*log(BMI) of twin 1

bmi2 7\*log(BMI) of twin 2

cohort Either “younger” or “older”

zygosity Zygosity factor with levels: MZFF, MZMM, DZFF, DZMM, DZOS

age1 Age of Twin 1

age2 Age of Twin 2

### Details

“zyg” codes twin-zygosity as follows: 1 == MZFF (i.e MZ females) 2 == MZMM (i.e MZ males)  
3 == DZFF 4 == DZMM 5 == DZOS opposite sex pairs

Note: zyg 6:10 are for an older cohort in the sample. So: 6 == MZFF (i.e MZ females) 7 == MZMM  
(i.e MZ males) 8 == DZFF 9 == DZMM 10 == DZOS opposite sex pairs

The “zygosity” and “cohort” variables take care of this for you (conventions differ).

### References

Martin, N. G. & Jardine, R. (1986). Eysenck’s contribution to behavior genetics. In S. Modgil & C. Modgil (Eds.), *Hans Eysenck: Consensus and Controversy*. Falmer Press: Lewes, Sussex.

Martin, N. G., Eaves, L. J., Heath, A. C., Jardine, R., Feingold, L. M., & Eysenck, H. J. (1986). Transmission of social attitudes. *Proceedings of the National Academy of Science*, **83**, 4364-4368.

### Examples

```
data(twinData)
str(twinData)
plot(wt1 ~ wt2, data = twinData)
selVars = c("bmi1", "bmi2")
mzData <- subset(twinData, zyg == 1, selVars)
dzData <- subset(twinData, zyg == 3, selVars)

# equivalently
mzData <- subset(twinData, zygosity == "MZFF", selVars)

# Disregard sex, pick older cohort
mz <- subset(twinData, zygosity %in% c("MZFF", "MZMM") & cohort == "older", selVars)
```

---

twin_NA_dot	<i>Twin data on weight and height</i>
-------------	---------------------------------------

---

**Description**

Data set used in some of OpenMx's examples.

**Usage**

```
data("twin_NA_dot")
```

**Format**

A data frame with 3808 observations on the following variables.

fam Family ID variable  
age Age of the twin pair. Range: 17 to 88.  
zyg Integer codes for zygosity and gender combinations  
part  
wt1 Weight in kilograms for twin 1  
wt2 Weight in kilograms for twin 2  
ht1 Height in meters for twin 1  
ht2 Height in meters for twin 2  
htwt1 Product of ht and wt for twin 1  
htwt2 Product of ht and wt for twin 2  
bmi1 Body Mass Index for twin 1  
bmi2 Body Mass Index for twin 2

**Details**

Same as [myTwinData](#) but has . as the missing data value instead of NA.

**Source**

Timothy Bates

**References**

The OpenMx User's guide can be found at <http://openmx.ssri.psu.edu/documentation>.

**Examples**

```
data(twin_NA_dot)
summary(twin_NA_dot)
# Note that all variables are treated as factors because of the missing data coding.
```



---

vec2diag	<i>Create Diagonal Matrix From Vector</i>
----------	---

---

**Description**

Given an input row or column vector, `vec2diag` returns a diagonal matrix with the input argument along the diagonal.

**Usage**

```
vec2diag(x)
```

**Arguments**

`x` a row or column vector.

**Details**

Similar to the function `diag`, except that the input argument is always treated as a vector of elements to place along the diagonal.

**See Also**

[diag2vec](#)

**Examples**

```
vec2diag(matrix(1:4, 1, 4))  
vec2diag(matrix(1:4, 4, 1))
```

---

vech	<i>Half-vectorization</i>
------	---------------------------

---

**Description**

This function returns the half-vectorization of an input matrix as a column vector.

**Usage**

```
vech(x)
```

**Arguments**

`x` an input matrix.

**Details**

The half-vectorization of an input matrix consists of the elements in the lower triangle of the matrix, including the elements along the diagonal of the matrix, as a column vector. The column vector is created by traversing the matrix in column-major order.

**See Also**

[vech2full](#), [vechs](#), [rvectorize](#), [cvectorize](#)

**Examples**

```
vech(matrix(1:9, 3, 3))  
vech(matrix(1:12, 3, 4))
```

---

vech2full

*Inverse Half-vectorization*

---

**Description**

This function returns the symmetric matrix constructed from a half-vectorization.

**Usage**

```
vech2full(x)
```

**Arguments**

`x` an input single column or single row matrix.

**Details**

The half-vectorization of an input matrix consists of the elements in the lower triangle of the matrix, including the elements along the diagonal of the matrix, as a column vector. The column vector is created by traversing the matrix in column-major order. The inverse half-vectorization takes a vector and reconstructs a symmetric matrix such that `vech2full(vech(x))` is identical to `x` if `x` is symmetric.

Note that very few vectors have the correct number of elements to construct a symmetric matrix. For example, vectors with 1, 3, 6, 10, and 15 elements can be used to make a symmetric matrix, but none of the other numbers between 1 and 15 can. An error is thrown if the number of elements in `x` cannot be used to make a symmetric matrix.

**See Also**

[vechs2full](#), [vech](#), [vechs](#), [rvectorize](#), [cvectorize](#)

**Examples**

```
vech2full(1:10)

matrix(1:16, 4, 4)
vech(matrix(1:16, 4, 4))
vech2full(vech(matrix(1:16, 4, 4)))
```

---

vechs	<i>Strict Half-vectorization</i>
-------	----------------------------------

---

**Description**

This function returns the strict half-vectorization of an input matrix as a column vector.

**Usage**

```
vechs(x)
```

**Arguments**

x                    an input matrix.

**Details**

The half-vectorization of an input matrix consists of the elements in the lower triangle of the matrix, excluding the elements along the diagonal of the matrix, as a column vector. The column vector is created by traversing the matrix in column-major order.

**See Also**

[vech](#), [rvectorize](#), [cvectorize](#)

**Examples**

```
vechs(matrix(1:9, 3, 3))
vechs(matrix(1:12, 3, 4))
```

---

`vechs2full`*Inverse Strict Half-vectorization*

---

**Description**

This function returns the symmetric matrix constructed from a strict half-vectorization.

**Usage**

```
vechs2full(x)
```

**Arguments**

`x` an input single column or single row matrix.

**Details**

The strict half-vectorization of an input matrix consists of the elements in the lower triangle of the matrix, excluding the elements along the diagonal of the matrix, as a column vector. The column vector is created by traversing the matrix in column-major order. The inverse strict half-vectorization takes a vector and reconstructs a symmetric matrix such that `vechs2full(vechs(x))` is equal to `x` with zero along the diagonal if `x` is symmetric.

Note that very few vectors have the correct number of elements to construct a symmetric matrix. For example, vectors with 1, 3, 6, 10, and 15 elements can be used to make a symmetric matrix, but none of the other numbers between 1 and 15 can. An error is thrown if the number of elements in `x` cannot be used to make a symmetric matrix.

**See Also**

[vech2full](#), [vech](#), [vechs](#), [rvectorize](#), [cvectorize](#)

**Examples**

```
vechs2full(1:10)

matrix(1:16, 4, 4)
vechs(matrix(1:16, 4, 4))
vechs2full(vechs(matrix(1:16, 4, 4)))
```

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