

# Package ‘CDM’

May 13, 2022

**Type** Package

**Title** Cognitive Diagnosis Modeling

**Version** 8.1-12

**Date** 2022-05-12 13:47:57

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## Description

Functions for cognitive diagnosis modeling and multidimensional item response modeling for dichotomous and polytomous item responses. This package enables the estimation of the DINA and DINO model (Junker & Sijtsma, 2001, <doi:10.1177/01466210122032064>), the multiple group (polytomous) GDINA model (de la Torre, 2011, <doi:10.1007/s11336-011-9207-7>), the multiple choice DINA model (de la Torre, 2009, <doi:10.1177/0146621608320523>), the general diagnostic model (GDM; von Davier, 2008, <doi:10.1348/000711007X193957>), the structured latent class model (SLCA; Formann, 1992, <doi:10.1080/01621459.1992.10475229>) and regularized latent class analysis (Chen, Li, Liu, & Ying, 2017, <doi:10.1007/s11336-016-9545-6>). See George, Robitzsch, Kiefer, Gross, and Uenlue (2017) <doi:10.18637/jss.v074.i02> or Robitzsch and George (2019, <doi:10.1007/978-3-030-05584-4\_26>) for further details on estimation and the package structure. For tutorials on how to use the CDM package see George and Robitzsch (2015, <doi:10.20982/tqmp.11.3.p189>) as well as Ravand and Robitzsch (2015).

**Depends** R (>= 3.1), mvtnorm

**Imports** graphics, grDevices, methods, polycor, Rcpp, stats, utils

**Suggests** BIFIEsurvey, lattice, MASS, miceadds, ROI, sfsmisc

**LinkingTo** Rcpp, RcppArmadillo

**Enhances** dina, GDINA, mirt, rrum

**LazyLoad** yes

**LazyData** yes

**URL** <https://github.com/alexanderrobitzsch/CDM>,  
<https://sites.google.com/site/alexanderrobitzsch2/software>

**License** GPL (>= 2)

**BugReports** <https://github.com/alexanderrobitzsch/CDM/issues?state=open>

**NeedsCompilation** yes

**Repository** CRAN

**Date/Publication** 2022-05-13 08:50:14 UTC

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## Description

Functions for cognitive diagnosis modeling and multidimensional item response modeling for dichotomous and polytomous item responses. This package enables the estimation of the DINA and DINO model (Junker & Sijtsma, 2001, <doi:10.1177/01466210122032064>), the multiple group (polytomous) GDINA model (de la Torre, 2011, <doi:10.1007/s11336-011-9207-7>), the multiple choice DINA model (de la Torre, 2009, <doi:10.1177/0146621608320523>), the general diagnostic model (GDM; von Davier, 2008, <doi:10.1348/000711007X193957>), the structured latent class model (SLCA; Formann, 1992, <doi:10.1080/01621459.1992.10475229>) and regularized latent class analysis (Chen, Li, Liu, & Ying, 2017, <doi:10.1007/s11336-016-9545-6>). See George, Robitzsch, Kiefer, Gross, and Uenlue (2017) <doi:10.18637/jss.v074.i02> or Robitzsch and George (2019, <doi:10.1007/978-3-030-05584-4\_26>) for further details on estimation and the package structure. For tutorials on how to use the CDM package see George and Robitzsch (2015, <doi:10.20982/tqmp.11.3.p189>) as well as Ravand and Robitzsch (2015).

## Details

Cognitive diagnosis models (CDMs) are restricted latent class models. They represent model-based classification approaches, which aim at assigning respondents to different attribute profile groups. The latent classes correspond to the possible attribute profiles, and the conditional item parameters model atypical response behavior in the sense of slipping and guessing errors. The core CDMs in particular differ in the utilized condensation rule, conjunctive / non-compensatory versus disjunctive / compensatory, where in the model structure these two types of response error parameters enter and what restrictions are imposed on them. The confirmatory character of CDMs is apparent in the Q-matrix, which can be seen as an operationalization of the latent concepts of an underlying theory. The Q-matrix allows incorporating qualitative prior knowledge and typically has as its rows the items and as the columns the attributes, with entries 1 or 0, depending on whether an attribute is measured by an item or not, respectively.

CDMs as compared to common psychometric models (e.g., IRT) contain categorical instead of continuous latent variables. The results of analyses using CDMs differ from the results obtained under continuous latent variable models. CDMs estimate in a direct manner the probabilistic attribute profile of a respondent, that is, the multivariate vector of the conditional probabilities for possessing the individual attributes, given her / his response pattern. Based on these probabilities, simplified deterministic attribute profiles can be derived, showing whether an individual attribute is essentially possessed or not by a respondent. As compared to alternative two-step discretization approaches, which estimate continuous scores and discretize the continua based on cut scores, with CDMs the classification error can generally be reduced.

The package CDM implements parameter estimation procedures for the DINA and DINO model (e.g., de la Torre & Douglas, 2004; Junker & Sijtsma, 2001; Templin & Henson, 2006; the generalized DINA model for dichotomous attributes (GDINA, de la Torre, 2011) and for polytomous attributes (pGDINA, Chen & de la Torre, 2013); the general diagnostic model (GDM, von Davier, 2008) and its extension to the multidimensional latent class IRT model (Bartolucci, 2007), the structure latent class model (Formann, 1992), and tools for analyzing data under the models. These

and related concepts are explained in detail in the book about diagnostic measurement and CDMs by Rupp, Templin and Henson (2010), and in such survey articles as DiBello, Roussos and Stout (2007) and Rupp and Templin (2008).

The package CDM is implemented based on the S3 system. It comes with a namespace and consists of several external functions (functions the package exports). The package contains a utility method for the simulation of artificial data based on a CDM model (`sim.din`). It also contains seven internal functions (functions not exported by the package): this are `plot`, `print`, and `summary` methods for objects of the class `din` (`plot.din`, `print.din`, `summary.din`), a `print` method for objects of the class `summary.din` (`print.summary.din`), and three functions for checking the input format and computing intermediate information. The features of the package CDM are illustrated with an accompanying real dataset and Q-matrix (`fraction.subtraction.data` and `fraction.subtraction.qmatrix`) and artificial examples (`Data-sim`).

See George et al. (2016) and Robitzsch and George (2019) for an overview and some computational details of the CDM package.

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### See Also

- See the **GDINA** package for comprehensive functions for the GDINA model.
- See also the **ACTCD** and **NPCD** packages for nonparametric cognitive diagnostic models.
- See the **dina** package for estimating the DINA model with a Gibbs sampler.

### Examples

```
##
## *****
## ** CDM 2.5-16 (2013-11-29) **
## ** Cognitive Diagnostic Models **
## *****
##
```

---

anova

*Likelihood Ratio Test for Model Comparisons*

---

### Description

This function compares two models estimated with `din`, `gdina` or `gdm` using a likelihood ratio test.

### Usage

```
## S3 method for class 'din'
anova(object,...)

## S3 method for class 'gdina'
anova(object,...)

## S3 method for class 'gdm'
```

```

anova(object,...)

## S3 method for class 'mcdina'
anova(object,...)

## S3 method for class 'reglca'
anova(object,...)

## S3 method for class 'slca'
anova(object,...)

```

### Arguments

```

object      Two objects of class din, gdina, mcdina, slca, gdm, reglca
...         Further arguments to be passed

```

### Note

This function is based on [IRT.anova](#).

### See Also

[din](#), [gdina](#), [gdm](#), [mcdina](#), [slca](#)

### Examples

```

#####
# EXAMPLE 1: anova with din objects
#####

# Model 1
d1 <- CDM::din(sim.dina, q.matr=sim.qmatrix )
# Model 2 with equal guessing and slipping parameters
d2 <- CDM::din(sim.dina, q.matr=sim.qmatrix, guess.equal=TRUE, slip.equal=TRUE)
# model comparison
anova(d1,d2)
##      Model  loglike Deviance Npars      AIC      BIC  Chisq df  p
##  2      d2 -2176.482 4352.963     9 4370.963 4406.886 268.2071 16 0
##  1      d1 -2042.378 4084.756    25 4134.756 4234.543      NA NA NA

## Not run:
#####
# EXAMPLE 2: anova with gdina objects
#####

# Model 3: GDINA model
d3 <- CDM::gdina( sim.dina, q.matr=sim.qmatrix )

# Model 4: DINA model
d4 <- CDM::gdina( sim.dina, q.matr=sim.qmatrix, rule="DINA")

```

```
# model comparison
anova(d3,d4)
##      Model  loglike Deviance Npars      AIC      BIC  Chisq df      p
##    2     d4 -2042.293 4084.586   25 4134.586 4234.373 31.31995 16 0.01224
##    1     d3 -2026.633 4053.267   41 4135.266 4298.917      NA NA      NA

## End(Not run)
```

---

cdi.kli

*Cognitive Diagnostic Indices based on Kullback-Leibler Information*


---

## Description

This function computes several cognitive diagnostic indices grounded on the Kullback-Leibler information (Rupp, Henson & Templin, 2009, Ch. 13) at the test, item, attribute and item-attribute level. See Henson and Douglas (2005) and Henson, Roussos, Douglas and He (2008) for more details.

## Usage

```
cdi.kli(object)

## S3 method for class 'cdi.kli'
summary(object, digits=2, ...)
```

## Arguments

object	Object of class <code>din</code> or <code>gdina</code> . For the summary method, it is the result of <code>cdi.kli</code> .
digits	Number of digits for rounding
...	Further arguments to be passed

## Value

A list with following entries

test_disc	Test discrimination which is the sum of all global item discrimination indices
attr_disc	Attribute discriminations
glob_item_disc	Global item discriminations (Cognitive diagnostic index)
attr_item_disc	Attribute-specific item discrimination
KLI	Array with Kullback-Leibler informations of all items (first dimension) and skill classes (in the second and third dimension)
skillclasses	Matrix containing all used skill classes in the model
hdist	Matrix containing Hamming distance between skill classes
pjk	Used probabilities
q.matrix	Used Q-matrix
summary	Data frame with test- and item-specific discrimination statistics



## References

- Henson, R., DiBello, L., & Stout, B. (2018). A generalized approach to defining item discrimination for DCMs. *Measurement: Interdisciplinary Research and Perspectives*, 16(1), 18-29. <http://dx.doi.org/10.1080/15366367.2018.15366367>
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- Rupp, A. A., Templin, J., & Henson, R. A. (2010). *Diagnostic Measurement: Theory, Methods, and Applications*. New York: The Guilford Press.

## See Also

- See [discrim.index](#) for computing discrimination indices at the probability metric.
- See Henson, DiBello and Stout (2018) for an overview of different discrimination indices.

## Examples

```
#####
# EXAMPLE 1: Examples based on CDM::sim.dina
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

mod <- CDM::din( sim.dina, q.matrix=sim.qmatrix )
summary(mod)
## Item parameters
##      item guess slip  IDI rmsea
## Item1 Item1 0.086 0.210 0.704 0.014
## Item2 Item2 0.109 0.239 0.652 0.034
## Item3 Item3 0.129 0.185 0.686 0.028
## Item4 Item4 0.226 0.218 0.556 0.019
## Item5 Item5 0.059 0.000 0.941 0.002
## Item6 Item6 0.248 0.500 0.252 0.036
## Item7 Item7 0.243 0.489 0.268 0.041
## Item8 Item8 0.278 0.125 0.597 0.109
## Item9 Item9 0.317 0.027 0.656 0.065

cmod <- CDM::cdi.kli( mod )

# attribute discrimination indices
round( cmod$attr_disc, 3 )
##      V1      V2      V3
##  1.966  2.506 11.169

# look at global item discrimination indices
round( cmod$glob_item_disc, 3 )
## > round( cmod$glob_item_disc, 3 )
## Item1 Item2 Item3 Item4 Item5 Item6 Item7 Item8 Item9
##  0.594 0.486 0.533 0.465 5.913 0.093 0.040 0.397 0.656
```

```

# correlation of IDI and global item discrimination
stats::cor( cmod$glob_item_disc, mod$IDI )
## [1] 0.6927274

# attribute-specific item indices
round( cmod$attr_item_disc, 3 )
##           V1    V2    V3
## Item1 0.648 0.648 0.000
## Item2 0.000 0.530 0.530
## Item3 0.581 0.000 0.581
## Item4 0.697 0.000 0.000
## Item5 0.000 0.000 8.870
## Item6 0.000 0.140 0.000
## Item7 0.040 0.040 0.040
## Item8 0.000 0.433 0.433
## Item9 0.000 0.715 0.715

## Note that attributes with a zero entry for an item
## do not differ from zero for the attribute specific item index

```

---

CDM-utilities

*Utility Functions in CDM*


---

## Description

Utility functions in CDM.

## Usage

```

## requireNamespace with package message for needed installation
CDM_require_namespace(pkg)
## attach internal function in a package
cdm_attach_internal_function(pack, fun)

## print function in summary
cdm_print_summary_data_frame(obji, from=NULL, to=NULL, digits=3, rownames_null=FALSE)
## print summary call
cdm_print_summary_call(object, call_name="call")
## print computation time
cdm_print_summary_computation_time(object, time_name="time", time_start="s1",
                                   time_end="s2")

## string vector of matrix entries
cdm_matrixstring( matr, string )

## mvtnorm::rmvnorm with vector conversion for n=1
CDM_rmvnorm(n, mean=NULL, sigma, ...)
## fit univariate and multivariate normal distribution

```

```
cdm_fit_normal(x, w)

## fit unidimensional factor analysis by unweighted least squares
cdm_fa1(Sigma, method=1, maxit=50, conv=1E-5)

## another rbind.fill implementation
CDM_rbind_fill( x, y )
## fills a vector row-wise into a matrix
cdm_matrix2( x, nrow )
## fills a vector column-wise into a matrix
cdm_matrix1( x, ncol )

## SCAD thresholding operator
cdm_penalty_threshold_scad(beta, lambda, a=3.7)
## lasso thresholding operator
cdm_penalty_threshold_lasso(val, eta )
## ridge thresholding operator
cdm_penalty_threshold_ridge(beta, lambda)
## elastic net threshold operator
cdm_penalty_threshold_elnet( beta, lambda, alpha )
## SCAD-L2 thresholding operator
cdm_penalty_threshold_scadL2(beta, lambda, alpha, a=3.7)
## truncated L1 penalty thresholding operator
cdm_penalty_threshold_tlp( beta, tau, lambda )
## MCP thresholding operator
cdm_penalty_threshold_mcp(beta, lambda, a=3.7)

## general thresholding operator for regularization
cdm_parameter_regularization(x, regular_type, regular_lam, regular_alpha=NULL,
                             regular_tau=NULL )
## values of penalty function
cdm_penalty_values(x, regular_type, regular_lam, regular_tau=NULL,
                  regular_alpha=NULL)
## thresholding operators regularization
cdm_parameter_regularization(x, regular_type, regular_lam, regular_alpha=NULL,
                             regular_tau=NULL)

## utility functions for P-EM acceleration
cdm_pem_inits(parmlist)
cdm_pem_inits_assign_parmlist(pem_pars, envir)
cdm_pem_acceleration( iter, pem_parameter_index, pem_parameter_sequence, pem_pars,
                     PEM_itermax, parmlist, ll_fct, ll_args, deviance.history=NULL )
cdm_pem_acceleration_assign_output_parameters(res_ll_fct, vars, envir, update)

## approximation of absolute value function and its derivative
abs_approx(x, eps=1e-05)
abs_approx_D1(x, eps=1e-05)
```

```
## information criteria
cdm_calc_information_criteria(ic)
cdm_print_summary_information_criteria(object, digits_crit=0, digits_penalty=2)

## string pasting
cat_paste(...)
```

### Arguments

pkg	An R package
pack	An R package
fun	An R function
obji	Object
from	Integer
to	Integer
digits	Number of digits used for printing
rownames_null	Logical
call_name	Character
time_name	Character
time_start	Character
time_end	Character
matr	Matrix
string	String
object	Object
n	Integer
mean	Mean vector or matrix if separate means for cases are provided. In this case, n can be missing.
sigma	Covariance matrix
...	More arguments to be passed (or a list of arguments)
x	Matrix or vector
y	Matrix or vector
w	Vector of sampling weights
nrow	Integer
ncol	Integer
Sigma	Covariance matrix
method	Method 1 indicates estimation of different item loadings, method 2 estimation of same item loadings.
maxit	Maximum number of iterations
conv	Convergence criterion
beta	Numeric

lambda	Regularization parameter
alpha	Regularization parameter
a	Parameter
tau	Regularization parameter
val	Numeric
eta	Regularization parameter
regular_type	Type of regularization
regular_lam	Regularization parameter $\lambda$
regular_tau	Regularization parameter $\tau$
regular_alpha	Regularization parameter $\alpha$
parmlist	List containing parameters
pem_pars	Vector containing parameter names
envir	Environment
update	Logical
iter	Iteration number
pem_parameter_index	List with parameter indices
pem_parameter_sequence	List with updated parameter sequence
PEM_itermax	Maximum number of iterations for PEM
ll_fct	Name of log-likelihood function
ll_args	Arguments of log-likelihood function
deviance.history	Deviance history, a data frame.
res_ll_fct	Result of maximized log-likelihood function
vars	Vector containing parameter names
eps	Numeric
ic	List
digits_crit	Integer
digits_penalty	Integer

---

 cdm.est.class.accuracy

*Classification Reliability in a CDM*


---

### Description

This function computes the classification accuracy and consistency originally proposed by Cui, Gierl and Chang (2012; see also Wang et al., 2015). The function computes both statistics by estimators of Johnson and Sinharay (2018; see also Sinharay & Johnson, 2019) and simulation based estimation.

### Usage

```
cdm.est.class.accuracy(cdmobj, n.sims=0, version=2)
```

### Arguments

cdmobj	Object of class <code>din</code> or <code>gdina</code>
n.sims	Number of simulated persons. If <code>n.sims=0</code> , then the number of persons in the original data is used as the sample size. In case of missing item responses, for every simulated dataset this sample size is used.
version	Correct classification reliability statistics can be obtained using the default <code>version=2</code> . For backward compatibility, <code>version=1</code> contains estimators for <b>CDM</b> ( $\leq 6.2$ ) which have been shown to be biased (Johnson & Sinharay, 2018).

### Details

The item parameters and the probability distribution of latent classes is used as the basis of the simulation. Accuracy and consistency is estimated for both MLE and MAP classification estimators. In addition, classification accuracy measures are available for the separate classification of all skills.

### Value

A data frame for MLE, MAP and MAP (Skill 1, ..., Skill  $K$ ) classification reliability for the whole latent class pattern and marginal skill classification with following columns:

Pa_est	Classification accuracy (Cui et al., 2012) using the estimator of Johnson and Sinharay, 2018
Pa_sim	Classification accuracy based on simulated data (only for <code>din</code> models)
Pc	Classification consistency (Cui et al., 2012) using the estimator of Johnson and Sinharay, 2018
Pc_sim	Classification consistency based on simulated data (only for <code>din</code> models)

## References

- Cui, Y., Gierl, M. J., & Chang, H.-H. (2012). Estimating classification consistency and accuracy for cognitive diagnostic assessment. *Journal of Educational Measurement*, 49, 19-38. doi: [10.1111/j.17453984.2011.00158.x](https://doi.org/10.1111/j.17453984.2011.00158.x)
- Johnson, M. S., & Sinharay, S. (2018). Measures of agreement to assess attribute-level classification accuracy and consistency for cognitive diagnostic assessments. *Journal of Educational Measurement*, 45(4), 635-664. doi: [10.1111/jedm.12196](https://doi.org/10.1111/jedm.12196)
- Sinharay, S., & Johnson, M. S. (2019). Measures of agreement: Reliability, classification accuracy, and classification consistency. In M. von Davier & Y.-S. Lee (Eds.). *Handbook of diagnostic classification models* (pp. 359-377). Cham: Springer. doi: [10.1007/9783030055844\\_17](https://doi.org/10.1007/9783030055844_17)
- Wang, W., Song, L., Chen, P., Meng, Y., & Ding, S. (2015). Attribute-level and pattern-level classification consistency and accuracy indices for cognitive diagnostic assessment. *Journal of Educational Measurement*, 52(4), 457-476. doi: [10.1111/jedm.12096](https://doi.org/10.1111/jedm.12096)

## Examples

```
## Not run:
#####
# EXAMPLE 1: DINO data example
#####

data(sim.dino, package="CDM")
data(sim.qmatrix, package="CDM")

####
# Model 1: estimate DINO model with din
mod1 <- CDM::din( sim.dino, q.matrix=sim.qmatrix, rule="DINO")
# estimate classification reliability
cdm.est.class.accuracy( mod1, n.sims=5000)

####
# Model 2: estimate DINO model with gdina
mod2 <- CDM::gdina( sim.dino, q.matrix=sim.qmatrix, rule="DINO")
# estimate classification reliability
cdm.est.class.accuracy( mod2 )

m1 <- mod1$coef[, c("guess", "slip" ) ]
m2 <- mod2$coef
m2 <- cbind( m1, m2[ seq(1,18,2), "est" ],
            1 - m2[ seq(1,18,2), "est" ] - m2[ seq(2,18,2), "est" ] )
colnames(m2) <- c("g.M1", "s.M1", "g.M2", "s.M2" )
## > round( m2, 3 )
##      g.M1  s.M1  g.M2  s.M2
## Item1 0.109 0.192 0.109 0.191
## Item2 0.073 0.234 0.072 0.234
## Item3 0.139 0.238 0.146 0.238
## Item4 0.124 0.065 0.124 0.009
## Item5 0.125 0.035 0.125 0.037
## Item6 0.214 0.523 0.214 0.529
## Item7 0.193 0.514 0.192 0.514
```

```

## Item8 0.246 0.100 0.246 0.100
## Item9 0.201 0.032 0.195 0.032
# Note that s (the slipping parameter) substantially differs for Item4
# for DINO estimation in 'din' and 'gdina'

## End(Not run)

```

---

coef

*Extract Estimated Item Parameters and Skill Class Distribution Parameters*


---

### Description

Extracts the estimated parameters from either `din`, `gdina`, `gdina` or `gdm` objects.

### Usage

```

## S3 method for class 'din'
coef(object, ...)

## S3 method for class 'gdina'
coef(object, ...)

## S3 method for class 'mcdina'
coef(object, ...)

## S3 method for class 'gdm'
coef(object, ...)

## S3 method for class 'slca'
coef(object, ...)

```

### Arguments

<code>object</code>	An object inheriting from either class <code>din</code> , class <code>gdina</code> , class <code>mcdina</code> , class <code>slca</code> or class <code>gdm</code> .
<code>...</code>	Additional arguments to be passed.

### Value

A vector, a matrix or a data frame of the estimated parameters for the fitted model.

### See Also

[din](#), [gdina](#), [gdm](#), [mcdina](#), [slca](#)



**Examples**

```

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

# DINA model
d1 <- CDM::din( sim.dina, q.matrix=sim.qmatrix)
coef(d1)

## Not run:
# GDINA model
d2 <- CDM::gdina( sim.dina, q.matrix=sim.qmatrix)
coef(d2)

# GDM model
theta.k <- seq(-4,4,len=11)
d3 <- CDM::gdm( sim.dina, irtmodel="2PL", theta.k=theta.k,
               Qmatrix=as.matrix(sim.qmatrix), centered.latent=TRUE)
coef(d3)

## End(Not run)

```

Data-sim

*Artificial Data: DINA and DINO***Description**

Artificial data: dichotomously coded fictitious answers of 400 respondents to 9 items assuming 3 underlying attributes.

**Usage**

```

data(sim.dina)
data(sim.dino)
data(sim.qmatrix)

```

**Format**

The `sim.dina` and `sim.dino` data sets include dichotomous answers of  $N = 400$  respondents to  $J = 9$  items, thus they are  $400 \times 9$  data matrices. For both data sets  $K = 3$  attributes are assumed to underlie the process of responding, stored in `sim.qmatrix`.

The `sim.dina` data set is simulated according to the DINA condensation rule, whereas the `sim.dino` data set is simulated according to the DINO condensation rule. The slipping errors for the items 1 to 9 in both data sets are 0.20, 0.20, 0.20, 0.20, 0.00, 0.50, 0.50, 0.10, 0.03 and the guessing errors are 0.10, 0.125, 0.15, 0.175, 0.2, 0.225, 0.25, 0.275, 0.3. The attributes are assumed to be mastered with expected probabilities of -0.4, 0.2, 0.6, respectively. The correlation of the attributes is 0.3 for attributes 1 and 2, 0.4 for attributes 1 and 3 and 0.1 for attributes 2 and 3.

**Example Index**

*Dataset sim.dina*

[anova](#) (Examples 1, 2), [cdi.kli](#) (Example 1), [din](#) (Examples 2, 4, 5), [gdina](#) (Example 1), [itemfit.sx2](#) (Example 2), [modelfit.cor.din](#) (Example 1)

*Dataset sim.dino*

[cdm.est.class.accuracy](#) (Example 1), [din](#) (Example 3), [gdina](#) (Examples 2, 3, 4),

**References**

Rupp, A. A., Templin, J. L., & Henson, R. A. (2010) *Diagnostic Measurement: Theory, Methods, and Applications*. New York: The Guilford Press.

---

data.cdm

*Several Datasets for the CDM Package*

---

**Description**

Several datasets for the **CDM** package

**Usage**

```
data(data.cdm01)
data(data.cdm02)
data(data.cdm03)
data(data.cdm04)
data(data.cdm05)
data(data.cdm06)
data(data.cdm07)
data(data.cdm08)
data(data.cdm09)
data(data.cdm10)
```

**Format**

- Dataset data.cdm01

This dataset is a multiple choice dataset and used in the [mcdina](#) function. The format is:

List of 3

\$ data : 'data.frame':

..\$ I1 : int [1:5003] 3 3 4 1 1 1 1 1 1 1 ...

..\$ I2 : int [1:5003] 1 1 3 1 1 2 1 1 2 1 ...

..\$ I3 : int [1:5003] 4 3 2 3 2 2 2 2 1 2 ...

..\$ I4 : int [1:5003] 3 3 3 2 2 2 2 3 3 1 ...

..\$ I5 : int [1:5003] 2 2 2 3 1 1 2 3 2 1 ...

..\$ I6 : int [1:5003] 3 1 1 1 1 2 1 1 1 1 ...

```

..$ I7 : int [1:5003] 1 1 2 2 1 3 1 1 1 3 ...
..$ I8 : int [1:5003] 1 1 1 1 1 2 1 4 3 3 ...
..$ I9 : int [1:5003] 3 2 1 1 1 1 3 3 1 3 ...
..$ I10: int [1:5003] 2 1 2 1 1 2 2 2 2 1 ...
..$ I11: int [1:5003] 2 2 2 2 1 2 1 2 1 1 ...
..$ I12: int [1:5003] 1 2 1 1 2 1 1 1 1 2 ...
..$ I13: int [1:5003] 2 1 1 1 2 1 2 2 1 1 ...
..$ I14: int [1:5003] 1 1 1 1 1 2 1 1 2 1 ...
..$ I15: int [1:5003] 1 2 1 1 1 1 1 1 1 1 ...
..$ I16: int [1:5003] 1 2 2 1 2 2 2 1 1 1 ...
..$ I17: int [1:5003] 1 1 1 1 1 1 1 1 1 1 ...
$group : int [1:5003] 1 1 1 1 1 1 1 1 1 1 ...
$q.matrix: 'data.frame':
..$ item : int [1:52] 1 1 1 1 2 2 2 2 3 3 ...
..$ categ: int [1:52] 1 2 3 4 1 2 3 4 1 2 ...
..$ A1 : int [1:52] 0 1 0 1 0 1 1 1 0 0 ...
..$ A2 : int [1:52] 0 0 1 1 0 0 0 1 0 0 ...
..$ A3 : int [1:52] 0 0 0 0 0 0 0 0 0 0 ...

```

- Dataset data.cdm02

Multiple choice dataset with a Q-matrix designed for polytomous attributes.

List of 2

```

$data : 'data.frame':
..$ I1 : int [1:3000] 3 3 4 1 1 1 1 1 1 1 ...
..$ I2 : int [1:3000] 1 1 3 1 1 2 1 1 2 1 ...
..$ I3 : int [1:3000] 4 3 2 3 2 2 2 2 1 2 ...
[...]
..$ B17: num [1:3000] 1 1 1 1 1 1 1 1 1 1 ...
..$ B18: num [1:3000] 1 1 1 1 2 2 2 2 2 2 ...
$q.matrix: 'data.frame':
..$ item : int [1:100] 1 1 1 1 2 2 2 2 3 3 ...
..$ categ: int [1:100] 1 2 3 4 1 2 3 4 1 2 ...
..$ A1 : num [1:100] 0 1 0 1 0 1 1 1 0 0 ...
..$ A2 : num [1:100] 0 0 1 1 0 0 0 1 0 0 ...
..$ A3 : num [1:100] 0 0 0 0 0 0 0 0 0 0 ...
..$ B1 : num [1:100] 0 0 0 0 0 0 0 0 0 0 ...

```

- Dataset data.cdm03:

This is a resimulated dataset from Chiu, Koehn and Wu (2016) where the data generating model is a reduced RUM model. See Example 1.

List of 2

```

$data : num [1:725, 1:16] 0 1 1 1 1 1 1 1 1 1 ...
..- attr(*, "dimnames")=List of 2
...$: NULL
...$: chr [1:16] "I01" "I02" "I03" "I04" ...
$qmatrix: 'data.frame': 16 obs. of 6 variables:
..$ item: Factor w/ 16 levels "I01","I02","I03",...: 1 2 3 4 5 6 7 8 9 10 ...
..$ A1 : int [1:16] 1 0 0 0 0 0 0 0 1 1 ...

```

```

..$ A2 : int [1:16] 0 1 0 0 1 1 0 0 0 0 ...
..$ A3 : int [1:16] 0 0 1 1 1 1 0 0 0 0 ...
..$ A4 : int [1:16] 0 0 0 0 0 0 1 1 1 1 ...
..$ A5 : int [1:16] 0 0 0 0 0 0 0 0 0 0 ...

```

- Dataset data.cdm04:

Simulated dataset for the sequential DINA model (as described in Ma & de la Torre, 2016). The dataset contains 1000 persons and 12 items which measure 2 skills.

List of 3

```

$ data : num [1:1000, 1:12] 0 0 0 1 1 0 0 0 0 0 ...
..- attr(*, "dimnames")=List of 2
...$: NULL
...$: chr [1:12] "I1" "I2" "I3" "I4" ...
$q.matrix1: 'data.frame': 18 obs. of 4 variables:
..$ Item: chr [1:18] "I1" "I2" "I3" "I4" ...
..$ Cat : int [1:18] 1 1 1 1 1 1 1 2 1 2 ...
..$ A1 : int [1:18] 1 1 1 0 0 0 1 1 1 1 ...
..$ A2 : int [1:18] 0 0 0 1 1 1 0 0 0 0 ...
$q.matrix2: 'data.frame': 18 obs. of 4 variables:
..$ Item: chr [1:18] "I1" "I2" "I3" "I4" ...
..$ Cat : int [1:18] 1 1 1 1 1 1 1 2 1 2 ...
..$ A1 : num [1:18] 1 1 1 0 0 0 1 1 1 1 ...
..$ A2 : num [1:18] 0 0 0 1 1 1 0 0 0 0 ...

```

- Dataset data.cdm05:

Example dataset used in Philipp, Strobl, de la Torre and Zeileis (2018). This dataset is a sub-dataset of the probability dataset in the **pks** package (Heller & Wickelmaier, 2013).

List of 3

```

$ data : 'data.frame': 504 obs. of 12 variables:
..$ b101: num [1:504] 1 1 1 1 1 1 1 1 1 1 ...
..$ b102: num [1:504] 1 1 1 1 1 1 1 1 1 1 ...
..$ b103: num [1:504] 1 1 1 1 1 1 1 1 1 1 ...
..$ b104: num [1:504] 1 1 1 1 0 1 0 0 0 1 ...
..$ b105: num [1:504] 1 0 1 1 1 1 0 1 1 1 ...
..$ b106: num [1:504] 1 1 1 1 1 1 1 1 1 1 ...
..$ b107: num [1:504] 1 1 1 1 1 1 1 1 1 1 ...
..$ b108: num [1:504] 1 1 1 1 1 1 0 1 1 1 ...
..$ b109: num [1:504] 1 1 0 1 1 0 0 1 1 0 ...
..$ b110: num [1:504] 0 0 0 1 0 0 0 0 0 1 ...
..$ b111: num [1:504] 0 1 0 0 0 1 0 0 0 0 ...
..$ b112: num [1:504] 1 1 0 1 0 1 0 1 0 0 ...
$q.matrix: 'data.frame': 12 obs. of 4 variables:
..$ pb: num [1:12] 1 0 0 0 1 1 1 1 1 0 ...
..$ cp: num [1:12] 0 1 0 0 1 1 0 0 0 1 ...
..$ un: num [1:12] 0 0 1 0 0 0 1 1 0 0 ...
..$ id: num [1:12] 0 0 0 1 0 0 0 0 1 1 ...
$ skills : Named chr [1:4] "how to calculate the classic probability "

```

```
..- attr(*, "names")=chr [1:4] "pb" "cp" "un" "id"
```

- Dataset data.cdm06:

Resimulated example dataset from Chen and Chen (2017).

List of 3

\$ data : 'data.frame': 2733 obs. of 15 variables:

```
..$ I01: num [1:2733] 1 0 0 1 0 0 0 1 1 1 ...
```

```
..$ I02: num [1:2733] 1 0 0 1 1 0 1 0 0 1 ...
```

```
..$ I03: num [1:2733] 0 0 0 1 1 0 1 0 1 0 ...
```

```
..$ I04: num [1:2733] 1 1 0 0 0 0 1 1 1 0 ...
```

```
..$ I05: num [1:2733] 1 0 1 1 0 1 1 1 1 1 ...
```

```
..$ I06: num [1:2733] 0 0 0 1 1 0 0 0 1 1 ...
```

```
..$ I07: num [1:2733] 1 1 1 0 0 1 1 0 1 1 ...
```

```
..$ I08: num [1:2733] 0 0 0 0 0 0 0 0 1 1 ...
```

```
..$ I09: num [1:2733] 1 0 0 1 1 1 0 1 0 1 ...
```

```
..$ I10: num [1:2733] 0 0 0 1 0 1 1 0 1 1 ...
```

```
..$ I11: num [1:2733] 0 1 0 1 1 1 1 0 1 1 ...
```

```
..$ I12: num [1:2733] 0 1 0 1 0 0 0 1 1 1 ...
```

```
..$ I13: num [1:2733] 0 0 1 1 0 1 0 0 0 1 ...
```

```
..$ I14: num [1:2733] 0 0 0 1 1 0 1 1 0 0 ...
```

```
..$ I15: num [1:2733] 0 0 0 1 0 0 1 0 1 1 ...
```

\$ q.matrix: 'data.frame': 15 obs. of 5 variables:

```
..$ RI: num [1:15] 1 1 1 0 1 1 1 1 0 0 ...
```

```
..$ JS: num [1:15] 1 0 0 1 0 0 0 0 0 1 ...
```

```
..$ GI: num [1:15] 0 1 0 1 0 0 1 1 1 1 ...
```

```
..$ II: num [1:15] 0 1 1 0 1 0 1 0 0 0 ...
```

```
..$ MI: num [1:15] 0 0 1 0 0 0 0 0 1 0 ...
```

\$ skills : chr [1:5, 1:2] "Retrieving explicit information" ...

```
..- attr(*, "dimnames")=List of 2
```

```
...$: chr [1:5] "RI" "JS" "GI" "II" ...
```

```
...$: chr [1:2] "skill" "description"
```

- Dataset data.cdm07:

This is a resimulated dataset from the social anxiety disorder data concerning social phobia which involve 13 dichotomous questions (Fang, Liu & Ling, 2017). The simulation was based on a latent class model with five classes. The dataset was also used in Chen, Li, Liu and Ying (2017).

```
$ data : num [1:863, 1:13] 1 0 1 1 1 1 1 1 1 1 ...
```

```
..- attr(*, "dimnames")=List of 2
```

```
...$: NULL
```

```
...$: chr [1:13] "I1" "I2" "I3" "I4" ...
```

\$ q.matrix: num [1:13, 1:3] 1 1 1 1 0 0 0 0 0 0 ...

```
..- attr(*, "dimnames")=List of 2
```

```
...$: chr [1:13] "I1" "I2" "I3" "I4" ...
```

```
...$: chr [1:3] "A1" "A2" "A3"
```

\$ items : atomic [1:13] 1 speaking in front of other people? ...

```
..- attr(*, "stem")=chr "Have you ever had a strong fear or avoidance of ..."
```

- Dataset data.cdm08:

This is a simulated dataset involving four skills and three misconceptions for the model for simultaneously identifying skills and misconceptions (SISM; Kuo, Chen & de la Torre, 2018). The Q-matrix follows the specification in their simulation study.

List of 2

\$ data : 'data.frame': 1300 obs. of 20 variables:

..\$ I01: num [1:1300] 1 0 0 1 1 1 1 1 1 1 ...

..\$ I02: num [1:1300] 0 0 0 0 1 1 1 1 1 1 ...

..\$ I03: num [1:1300] 0 0 0 0 1 1 1 1 1 1 ...

..\$ I04: num [1:1300] 1 1 0 1 0 1 1 0 1 1 ...

..\$ I05: num [1:1300] 1 1 1 0 1 1 0 1 1 1 ...

..[...]

..\$ I18: num [1:1300] 0 1 0 0 0 0 0 0 0 1 ...

..\$ I19: num [1:1300] 1 1 0 0 0 0 0 1 1 1 ...

..\$ I20: num [1:1300] 1 1 0 0 0 1 0 1 0 1 ...

\$ q.matrix: 'data.frame': 20 obs. of 7 variables:

..\$ S1: num [1:20] 1 0 0 0 0 0 0 1 0 0 ...

..\$ S2: num [1:20] 0 1 0 0 0 0 0 0 1 0 ...

..\$ S3: num [1:20] 0 0 1 0 0 0 0 0 0 1 ...

..\$ S4: num [1:20] 0 0 0 1 0 0 0 0 0 0 ...

..\$ B1: num [1:20] 0 0 0 0 1 0 0 1 1 0 ...

..\$ B2: num [1:20] 0 0 0 0 0 1 0 0 0 0 ...

..\$ B3: num [1:20] 0 0 0 0 0 0 1 0 0 1 ...

- Dataset data.cdm09: This is a simulated dataset involving polytomous skills which is adapted from the empirical example (proportional reasoning data) of Chen and de la Torre (2013).

List of 2

\$ data : num [1:500, 1:15] 1 0 1 1 0 1 1 1 1 1 ...

..- attr(\*, "dimnames")=List of 2

...\$: NULL

...\$: chr [1:15] "I1" "I2" "I3" "I4" ...

\$ q.matrix: 'data.frame': 15 obs. of 4 variables:

..\$ A1: int [1:15] 0 0 0 0 2 0 0 2 1 1 ...

..\$ A2: int [1:15] 1 0 2 0 0 1 2 0 1 1 ...

..\$ A3: int [1:15] 0 0 0 1 0 0 0 0 0 0 ...

..\$ A4: int [1:15] 0 1 1 0 0 0 0 0 0 0 ...

- Dataset data.cdm10: This is a simulated dataset involving a hierarchical skill structure. Skill A has four levels, skill B possesses two levels and skill C has three levels.

List of 2

\$ data : num [1:1500, 1:15] 1 1 0 0 0 1 1 0 0 1 ...

..- attr(\*, "dimnames")=List of 2

...\$: NULL

...\$: chr [1:15] "I1" "I2" "I3" "I4" ...

\$ q.matrix: num [1:15, 1:6] 1 1 1 1 1 1 0 0 0 0 ...

..- attr(\*, "dimnames")=List of 2

...\$: chr [1:15] "I1" "I2" "I3" "I4" ...

```
... .$ : chr [1:6] "A1" "A2" "A3" "B1" ...
```

## References

- Chen, H., & Chen, J. (2017). Cognitive diagnostic research on chinese students' English listening skills and implications on skill training. *English Language Teaching*, 10(12), 107-115. <http://dx.doi.org/10.5539/elt.v10n12p107>
- Chen, J., & de la Torre, J. (2013). A general cognitive diagnosis model for expert-defined polytomous attributes. *Applied Psychological Measurement*, 37, 419-437. <http://dx.doi.org/10.1177/0146621613479818>
- Chen, Y., Li, X., Liu, J., & Ying, Z. (2017). Regularized latent class analysis with application in cognitive diagnosis. *Psychometrika*, 82, 660-692. <http://dx.doi.org/10.1007/s11336-016-9545-6>
- Chiu, C.-Y., Koehn, H.-F., & Wu, H.-M. (2016). Fitting the reduced RUM with Mplus: A tutorial. *International Journal of Testing*, 16(4), 331-351. <http://dx.doi.org/10.1080/15305058.2016.1148038>
- Fang, G., Liu, J., & Ying, Z. (2017). On the identifiability of diagnostic classification models. *arXiv*, 1706.01240. <https://arxiv.org/abs/1706.01240>
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- Kuo, B.-C., Chen, C.-H., & de la Torre, J. (2018). A cognitive diagnosis model for identifying coexisting skills and misconceptions. *Applied Psychological Measurement*, 42(3), 179-191. <http://dx.doi.org/10.1177/0146621617722791>
- Ma, W., & de la Torre, J. (2016). A sequential cognitive diagnosis model for polytomous responses. *British Journal of Mathematical and Statistical Psychology*, 69(3), 253-275. <https://doi.org/10.1111/bmsp.12070>
- Philipp, M., Strobl, C., de la Torre, J., & Zeileis, A. (2018). On the estimation of standard errors in cognitive diagnosis models. *Journal of Educational and Behavioral Statistics*, 43(1), 88-115. <http://dx.doi.org/10.3102/1076998617719728>

## Examples

```
## Not run:
#####
# EXAMPLE 1: Reduced RUM model, Chiu et al. (2016)
#####

data(data.cdm03, package="CDM")
dat <- data.cdm03$data
qmatrix <- data.cdm03$qmatrix

#### Model 1: Reduced RUM
mod1 <- CDM::gdina( dat, q.matrix=qmatrix[,-1], rule="RRUM" )
summary(mod1)

#### Model 2: Additive model with identity link function
mod2 <- CDM::gdina( dat, q.matrix=qmatrix[,-1], rule="ACDM" )
summary(mod2)
```

```

**** Model 3: Additive model with logit link function
mod3 <- CDM::gdina( dat, q.matrix=qmatrix[,-1], rule="ACDM", linkfct="logit")
summary(mod3)

#####
# EXAMPLE 2: GDINA model - probability dataset from the pks package
#####

data(data.cdm05, package="CDM")
dat <- data.cdm05$data
Q <- data.cdm05$q.matrix

#* estimate model
mod1 <- CDM::gdina( dat, q.matrix=Q )
summary(mod1)

## End(Not run)

```

---

data.dcm	<i>Dataset from Book 'Diagnostic Measurement' of Rupp, Templin and Henson (2010)</i>
----------	--

---

## Description

Dataset from Chapter 9 of the book 'Diagnostic Measurement' (Rupp, Templin & Henson, 2010).

## Usage

```
data(data.dcm)
```

## Format

The format of the data is a list containing the dichotomous item response data data (10000 persons at 7 items) and the Q-matrix q.matrix (7 items and 3 skills):

```

List of 2
 $ data : 'data.frame':
 ..$ id: int [1:10000] 1 2 3 4 5 6 7 8 9 10 ...
 ..$ D1: num [1:10000] 0 0 0 0 1 0 1 0 0 1 ...
 ..$ D2: num [1:10000] 0 0 0 0 0 1 1 1 0 1 ...
 ..$ D3: num [1:10000] 1 0 1 0 1 1 0 0 0 1 ...
 ..$ D4: num [1:10000] 0 0 1 0 0 1 1 1 0 0 ...
 ..$ D5: num [1:10000] 1 0 0 0 1 1 1 0 1 0 ...
 ..$ D6: num [1:10000] 0 0 0 0 1 1 1 0 0 1 ...
 ..$ D7: num [1:10000] 0 0 0 0 0 1 1 0 1 1 ...
 $ q.matrix: num [1:7, 1:3] 1 0 0 1 1 0 1 0 1 0 ...
 ..- attr(*, "dimnames")=List of 2
 ...$ : chr [1:7] "D1" "D2" "D3" "D4" ...
 ...$ : chr [1:3] "skill1" "skill2" "skill3"

```



## Source

For supplementary material of the Rupp, Templin and Henson book (2010) see <http://dcm.coe.uga.edu/>.

The dataset was downloaded from <http://dcm.coe.uga.edu/supplemental/chapter9.html>.

## References

Rupp, A. A., Templin, J., & Henson, R. A. (2010). *Diagnostic Measurement: Theory, Methods, and Applications*. New York: The Guilford Press.

## Examples

```
## Not run:
data(data.dcm, package="CDM")

dat <- data.dcm$data[,-1]
Q <- data.dcm$q.matrix

#####
# Model 1: DINA model
#####
mod1 <- CDM::din( dat, q.matrix=Q )
summary(mod1)

#-----
# Model 1m: estimate model in mirt package
library(mirt)
library(sirt)

*** define theta grid of skills
# use the function skillspace.hierarchy just for convenience
hier <- "skill1 > skill2"
skillspace <- CDM::skillspace.hierarchy( hier, skill.names=colnames(Q) )
Theta <- as.matrix(skillspace$skillspace.complete)
*** create mirt model
mirtmodel <- mirt::mirt.model("
  skill1=1
  skill2=2
  skill3=3
  (skill1*skill2)=4
  (skill1*skill3)=5
  (skill2*skill3)=6
  (skill1*skill2*skill3)=7
  ")
*** mirt parameter table
mod.pars <- mirt::mirt( dat, mirtmodel, pars="values")
# use starting values of .20 for guessing parameter
ind <- which( mod.pars$name=="d" )
mod.pars[ind,"value"] <- stats::qlogis(.20) # guessing parameter on the logit metric
# use starting values of .80 for anti-slipping parameter
ind <- which( ( mod.pars$name %in% paste0("a",1:20 ) ) & (mod.pars$est) )
```

```

mod.pars[ind,"value"] <- stats::qlogis(.80) - stats::qlogis(.20)
mod.pars
  *** prior for the skill space distribution
I <- ncol(dat)
lca_prior <- function(Theta,Etable){
  TP <- nrow(Theta)
  if ( is.null(Etable) ){ prior <- rep( 1/TP, TP ) }
  if ( ! is.null(Etable) ){
    prior <- ( rowSums(Etable[, seq(1,2*I,2)]) + rowSums(Etable[,seq(2,2*I,2)]) )/I
  }
  prior <- prior / sum(prior)
  return(prior)
}

  *** estimate model in mirt
mod1m <- mirt::mirt(dat, mirtmodel, pars=mod.pars, verbose=TRUE,
  technical=list( customTheta=Theta, customPriorFun=lca_prior) )
  # The number of estimated parameters is incorrect because mirt does not correctly count
  # estimated parameters from the user customized prior distribution.
mod1m@nest <- as.integer(sum(mod.pars$est) + nrow(Theta) - 1)
  # extract log-likelihood
mod1m@logLik
  # compute AIC and BIC
( AIC <- -2*mod1m@logLik+2*mod1m@nest )
( BIC <- -2*mod1m@logLik+log(mod1m@Data$N)*mod1m@nest )
  *** extract item parameters
cmod1m <- sirt::mirt.wrapper.coef(mod1m)$coef
# compare estimated guessing and slipping parameters
dfr <- data.frame(   "din.guess"=mod1m$guess$est,
                    "mirt.guess"=plogis(cmod1m$d), "din.slip"=mod1m$slip$est,
                    "mirt.slip"=1-plogis( rowSums( cmod1m[, c("d", paste0("a",1:7) ) ] ) )
                    )
round(t(dfr),3)
##           [,1] [,2] [,3] [,4] [,5] [,6] [,7]
##  din.guess 0.217 0.193 0.189 0.135 0.143 0.135 0.162
##  mirt.guess 0.226 0.189 0.184 0.132 0.142 0.132 0.158
##  din.slip   0.338 0.331 0.334 0.220 0.222 0.211 0.042
##  mirt.slip  0.339 0.333 0.336 0.223 0.225 0.214 0.044

# compare estimated skill class distribution
dfr <- data.frame("din"=mod1m$attribute.patt$class.prob,
                  "mirt"=mod1m@Prior[[1]] )
round(t(dfr),3)
##           [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8]
##  din  0.113 0.083 0.094 0.092 0.064 0.059 0.065 0.429
##  mirt 0.116 0.074 0.095 0.064 0.095 0.058 0.066 0.433

  *** extract estimated classifications
fsc1m <- sirt::mirt.wrapper.fscores( mod1m )
#- estimated reliabilities
fsc1m$EAP.rel
##      skill1    skill2    skill3
##  0.5479942 0.5362595 0.5357961

```

```

#- estimated classifications: EAPs, MLEs and MAPs
head( round(fsc1m$person,3) )
##   case   M EAP.skill1 SE.EAP.skill1 EAP.skill2 SE.EAP.skill2 EAP.skill3 SE.EAP.skill3
## 1 1 0.286 0.508 0.500 0.067 0.251 0.820 0.384
## 2 2 0.000 0.162 0.369 0.191 0.393 0.190 0.392
## 3 3 0.286 0.200 0.400 0.211 0.408 0.607 0.489
## 4 4 0.000 0.162 0.369 0.191 0.393 0.190 0.392
## 5 5 0.571 0.802 0.398 0.267 0.443 0.928 0.258
## 6 6 0.857 0.998 0.045 1.000 0.019 1.000 0.020
##   MLE.skill1 MLE.skill2 MLE.skill3 MAP.skill1 MAP.skill2 MAP.skill3
## 1 1 0 1 0 1 0 1
## 2 0 0 0 0 0 0 0
## 3 0 0 1 0 0 0 1
## 4 0 0 0 0 0 0 0
## 5 1 0 1 1 0 1 1
## 6 1 1 1 1 1 1 1

#** estimate model fit in mirt
( fit1m <- mirt::M2( mod1m ) )

#*****
# Model 2: DINO model
#*****
mod2 <- CDM::din( dat, q.matrix=Q, rule="DINO" )
summary(mod2)

#*****
# Model 3: log-linear model (LCDM): this model is the GDINA model with the
# logit link function
#*****
mod3 <- CDM::gdina( dat, q.matrix=Q, link="logit" )
summary(mod3)

#*****
# Model 4: GDINA model with identity link function
#*****
mod4 <- CDM::gdina( dat, q.matrix=Q )
summary(mod4)

#*****
# Model 5: GDINA additive model identity link function
#*****
mod5 <- CDM::gdina( dat, q.matrix=Q, rule="ACDM" )
summary(mod5)

#*****
# Model 6: GDINA additive model logit link function
#*****
mod6 <- CDM::gdina( dat, q.matrix=Q, link="logit", rule="ACDM" )
summary(mod6)

#-----
# Model 6m: GDINA additive model in mirt package

```

```

# use data specifications from Model 1m)
*** create mirt model
mirtmodel <- mirt::mirt.model("
  skill1=1,4,5,7
  skill2=2,4,6,7
  skill3=3,5,6,7
  " )
*** mirt parameter table
mod.pars <- mirt::mirt( dat, mirtmodel, pars="values")
*** estimate model in mirt
# Theta and lca_prior as defined as in Model 1m
mod6m <- mirt::mirt(dat, mirtmodel, pars=mod.pars, verbose=TRUE,
  technical=list( customTheta=Theta, customPriorFun=lca_prior) )
mod6m@nest <- as.integer(sum(mod.pars$est) + nrow(Theta) - 1)
# extract log-likelihood
mod6m@logLik
# compute AIC and BIC
( AIC <- -2*mod6m@logLik+2*mod6m@nest )
( BIC <- -2*mod6m@logLik+log(mod6m@Data$N)*mod6m@nest )
*** skill distribution
mod6m@Prior[[1]]
*** extract item parameters
cm6m <- mirt.wrapper.coef(mod6m)$coef
print(cm6m,digits=4)
##      item  a1  a2  a3      d g u
##  1  D1 1.882 0.000 0.000 -0.9330 0 1
##  2  D2 0.000 2.049 0.000 -1.0430 0 1
##  3  D3 0.000 0.000 2.028 -0.9915 0 1
##  4  D4 2.697 2.525 0.000 -2.9925 0 1
##  5  D5 2.524 0.000 2.478 -2.7863 0 1
##  6  D6 0.000 2.818 2.791 -3.1324 0 1
##  7  D7 3.113 2.918 2.785 -4.2794 0 1

#####
# Model 7: Reduced RUM model
#####
mod7 <- CDM::gdina( dat, q.matrix=Q, rule="RRUM")
summary(mod7)

#####
# Model 8: latent class model with 3 classes and 4 sets of starting values
#####

#-- Model 8a: randomLCA package
library(randomLCA)
mod8a <- randomLCA::randomLCA( dat, nclass=3, verbose=TRUE, notrials=4)

#-- Model 8b: rasch.mirtlc function in sirt package
library(sirt)
mod8b <- sirt::rasch.mirtlc( dat, Nclasses=3, nstarts=4 )
summary(mod8a)
summary(mod8b)

```

```
## End(Not run)
```

---

data.dtmr	<i>DTMR Fraction Data (Bradshaw et al., 2014)</i>
-----------	---

---

## Description

This is a simulated dataset of the DTMR fraction data described in Bradshaw, Izsak, Templin and Jacobson (2014).

## Usage

```
data(data.dtmr)
```

## Format

The format is:

```
List of 5
 $ data : num [1:5000, 1:27] 0 0 0 0 0 1 0 0 1 1 ...
 ..- attr(*, "dimnames")=List of 2
 ... $ : NULL
 ... $ : chr [1:27] "M1" "M2" "M3" "M4" ...
 $ q.matrix : 'data.frame': 27 obs. of 4 variables:
 .. $ RU : int [1:27] 1 0 0 1 1 0 1 0 0 0 ...
 .. $ PI : int [1:27] 0 0 1 0 0 1 0 0 0 0 ...
 .. $ APP: int [1:27] 0 1 0 0 0 0 0 1 1 1 ...
 .. $ MC : int [1:27] 0 0 0 0 0 0 0 0 0 0 ...
 $ skill.distribution: 'data.frame': 16 obs. of 5 variables:
 .. $ RU : int [1:16] 0 0 0 0 0 0 0 0 1 1 ...
 .. $ PI : int [1:16] 0 0 0 0 1 1 1 1 0 0 ...
 .. $ APP: int [1:16] 0 0 1 1 0 0 1 1 0 0 ...
 .. $ MC : int [1:16] 0 1 0 1 0 1 0 1 0 1 ...
 .. $ freq: int [1:16] 1064 350 280 406 196 126 238 770 14 28 ...
 $ itempars : 'data.frame': 27 obs. of 7 variables:
 .. $ item : chr [1:27] "M1" "M2" "M3" "M4" ...
 .. $ lam0 : num [1:27] -1.12 0.59 -2.07 -1.19 -1.67 -3.81 -0.73 -0.62 -0.09 0.28 ...
 .. $ RU : num [1:27] 2.24 0 0 0.65 1.52 0 1.2 0 0 0 ...
 .. $ PI : num [1:27] 0 0 1.7 0 0 2.08 0 0 0 0 ...
 .. $ APP: num [1:27] 0 1.27 0 0 0 0 0 4.25 2.16 0.87 ...
 .. $ MC : num [1:27] 0 0 0 0 0 0 0 0 0 0 ...
 .. $ RU.PI: num [1:27] 0 0 0 0 0 0 0 0 0 0 ...
 $ sim_data :function(N, skill.distribution, itempars)
 ..- attr(*, "srcref")='srcref' int [1:8] 1 13 20 1 13 1 1 20
 ...- attr(*, "srcfile")=Classes 'srcfilecopy', 'srcfile' <environment: 0x00000000298a8ed0>
```

The attribute definition are as follows

RU: Referent units  
 PI: Partitioning and iterating attribute  
 APP: Appropriateness attribute  
 MC: Multiplicative Comparison attribute

## Source

Simulated dataset according to Bradshaw et al. (2014).

## References

Bradshaw, L., Izsak, A., Templin, J., & Jacobson, E. (2014). Diagnosing teachers' understandings of rational numbers: Building a multidimensional test within the diagnostic classification framework. *Educational Measurement: Issues and Practice*, 33, 2-14.

## Examples

```
## Not run:
#####
# EXAMPLE 1: Model comparisons data.dtmr
#####

data(data.dtmr, package="CDM")
data <- data.dtmr$data
q.matrix <- data.dtmr$q.matrix
I <- ncol(data)

### Model 1: LCDM
# define item wise rules
rule <- rep( "ACDM", I )
names(rule) <- colnames(data)
rule[ c("M14","M17") ] <- "GDINA2"
# estimate model
mod1 <- CDM::gdina( data, q.matrix, linkfct="logit", rule=rule)
summary(mod1)

### Model 2: DINA model
mod2 <- CDM::gdina( data, q.matrix, rule="DINA" )
summary(mod2)

### Model 3: RRUM model
mod3 <- CDM::gdina( data, q.matrix, rule="RRUM" )
summary(mod3)

#--- model comparisons

# LCDM vs. DINA
anova(mod1,mod2)
##      Model  loglike Deviance Npars      AIC      BIC  Chisq df  p
##  2 Model 2 -76570.89 153141.8    69 153279.8 153729.5 1726.645 10 0
##  1 Model 1 -75707.57 151415.1    79 151573.1 152088.0      NA NA NA
```

```

# LCDM vs. RRUM
anova(mod1,mod3)
##      Model  loglike Deviance Npars      AIC      BIC  Chisq df  p
##    2 Model 2 -75746.13 151492.3   77 151646.3 152148.1 77.10994 2 0
##    1 Model 1 -75707.57 151415.1   79 151573.1 152088.0      NA NA NA

#--- model fit
summary( CDM::modelfit.cor.din( mod1 ) )
## Test of Global Model Fit
##      type  value  p
##    1 max(X2) 7.74382 1.00000
##    2 abs(fcor) 0.04056 0.72707
##
## Fit Statistics
##      est
## MADcor 0.00959
## SRMSR 0.01217
## MX2 0.75696
## 100*MADRESIDCOV 0.20283
## MADQ3 0.02220

#####
# EXAMPLE 2: Simulating data of structure data.dtmr
#####

data(data.dtmr, package="CDM")

# draw sample of N=200
set.seed(87)
data.dtmr$sim_data(N=200, skill.distribution=data.dtmr$skill.distribution,
                  itempars=data.dtmr$itempars)

## End(Not run)

```

---

data.ecpe

*Dataset ECPE*


---

## Description

ECPE dataset from the Templin and Hoffman (2013) tutorial of specifying cognitive diagnostic models in Mplus.

## Usage

```
data(data.ecpe)
```

**Format**

The format of the data is a list containing the dichotomous item response data `data` (2922 persons at 28 items) and the Q-matrix `q.matrix` (28 items and 3 skills):

```
List of 2
 $ data : 'data.frame':
 ..$ id : int [1:2922] 1 2 3 4 5 6 7 8 9 10 ...
 ..$ E1 : int [1:2922] 1 1 1 1 1 1 1 0 1 1 ...
 ..$ E2 : int [1:2922] 1 1 1 1 1 1 1 1 1 1 ...
 ..$ E3 : int [1:2922] 1 1 1 1 1 1 1 1 1 1 ...
 ..$ E4 : int [1:2922] 0 1 1 1 1 1 1 1 1 1 ...
 [...]
 ..$ E27: int [1:2922] 1 1 1 1 1 1 1 0 1 1 ...
 ..$ E28: int [1:2922] 1 1 1 1 1 1 1 1 1 1 ...
 $ q.matrix: 'data.frame':
 ..$ skill1: int [1:28] 1 0 1 0 0 0 1 0 0 1 ...
 ..$ skill2: int [1:28] 1 1 0 0 0 0 0 1 0 0 ...
 ..$ skill3: int [1:28] 0 0 1 1 1 1 1 0 1 0 ...
```

The skills are

skill1: Morphosyntactic rules

skill2: Cohesive rules

skill3: Lexical rules.

**Details**

The dataset has been used in Templin and Hoffman (2013), and Templin and Bradshaw (2014).

**Source**

The dataset was downloaded from <http://psych.unl.edu/jtemplin/teaching/dcm/dcm12ncme/>.

**References**

Templin, J., & Bradshaw, L. (2014). Hierarchical diagnostic classification models: A family of models for estimating and testing attribute hierarchies. *Psychometrika*, *79*, 317-339.

Templin, J., & Hoffman, L. (2013). Obtaining diagnostic classification model estimates using Mplus. *Educational Measurement: Issues and Practice*, *32*, 37-50.

**See Also**

[GDINA: :ecpe](#)

**Examples**

```
## Not run:
data(data.ecpe, package="CDM")
```



```

dat <- data.ecpe$data[,-1]
Q <- data.ecpe$q.matrix

#### Model 1: LCDM model
mod1 <- CDM::gdina( dat, q.matrix=Q, link="logit")
summary(mod1)

#### Model 2: DINA model
mod2 <- CDM::gdina( dat, q.matrix=Q, rule="DINA")
summary(mod2)

# Model comparison using likelihood ratio test
anova(mod1,mod2)
##      Model  loglike Deviance Npars      AIC      BIC  Chisq df  p
##  2 Model 2 -42841.61 85683.23   63 85809.23 86185.97 206.0359 18 0
##  1 Model 1 -42738.60 85477.19   81 85639.19 86123.57      NA NA NA

#### Model 3: Hierarchical LCDM (HLCDM) | Templin and Bradshaw (2014)
#   Testing a linear hierarchy
hier <- "skill3 > skill2 > skill1"
skill.names <- colnames(Q)
# define skill space with hierarchy
skill.space <- CDM::skill.space.hierarchy( hier, skill.names=skill.names )
skill.space$skill.space.reduced
##      skill1 skill2 skill3
##  A000      0      0      0
##  A001      0      0      1
##  A011      0      1      1
##  A111      1      1      1
zeroprob.skill.classes <- skill.space$zeroprob.skill.classes

# define user-defined parameters in LCDM: hierarchical LCDM (HLCDM)
Mj.user <- mod1$Mj
# select items with require two attributes
items <- which( rowSums(Q) > 1 )
# modify design matrix for item parameters
for (ii in items){
  m1 <- Mj.user[[ii]]
  Mj.user[[ii]][[1]] <- (m1[[1]])[-2]
  Mj.user[[ii]][[2]] <- (m1[[2]])[-2]
}

# estimate model
#   note that avoid.zeroprob is set to TRUE to avoid algorithmic instabilities
mod3 <- CDM::gdina( dat, q.matrix=Q, link="logit",
  zeroprob.skill.classes=zeroprob.skill.classes, Mj=Mj.user,
  avoid.zeroprob=TRUE )
summary(mod3)

*****
*** estimate further models

#### Model 4: RRUM model

```

```

mod4 <- CDM::gdina( dat, q.matrix=Q, rule="RRUM")
summary(mod4)
# compare some models
IRT.compareModels(mod1, mod2, mod3, mod4 )

#### Model 5a: GDINA model with identity link
mod5a <- CDM::gdina( dat, q.matrix=Q, link="identity")
summary(mod5a)
#### Model 5b: GDINA model with logit link
mod5b <- CDM::gdina( dat, q.matrix=Q, link="logit")
summary(mod5b)
#### Model 5c: GDINA model with log link
mod5c <- CDM::gdina( dat, q.matrix=Q, link="log")
summary(mod5c)
# compare models
IRT.compareModels(mod5a, mod5b, mod5c)

## End(Not run)

```

---

data.fraction	<i>Fraction Subtraction Dataset with Different Subsets of Data and Different Q-Matrices</i>
---------------	---

---

## Description

Contains different sub-datasets of the fraction subtraction data of Tatsuoka with different Q-matrix specifications.

## Usage

```

data(data.fraction1)
data(data.fraction2)
data(data.fraction3)
data(data.fraction4)
data(data.fraction5)

```

## Format

- The dataset data.fraction1 is the fraction subtraction data set with 536 students and 15 items. The Q-matrix was defined in de la Torre (2009). This dataset is a list with the dataset (data) and the Q-matrix as entries.

The format is:

List of 2

```

$ data : 'data.frame':
..$ T01: int [1:536] 0 1 1 1 0 0 0 0 0 0 ...
..$ T02: int [1:536] 1 1 1 1 1 0 0 1 0 0 ...
..$ T03: int [1:536] 0 1 1 1 1 1 0 0 0 0 ...
..$ T04: int [1:536] 1 1 1 0 0 0 0 0 0 0 ...

```

```

..$ T05: int [1:536] 0 1 0 0 0 1 1 0 1 1 ...
..$ T06: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
..$ T07: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
..$ T08: int [1:536] 1 1 0 1 1 0 0 0 1 1 ...
..$ T09: int [1:536] 1 1 1 1 0 1 0 0 1 0 ...
..$ T10: int [1:536] 1 1 1 0 0 0 0 0 0 0 ...
..$ T11: int [1:536] 1 1 1 1 0 0 0 0 0 0 ...
..$ T12: int [1:536] 0 1 0 0 0 0 0 0 0 0 ...
..$ T13: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
..$ T14: int [1:536] 1 1 0 0 0 0 0 0 0 0 ...
..$ T15: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
$q.matrix: int [1:15, 1:5] 1 1 1 1 0 1 1 1 1 1 ...
.- attr(*, "dimnames")=List of 2
...$: chr [1:15] "T01" "T02" "T03" "T04" ...
...$: chr [1:5] "QT1" "QT2" "QT3" "QT4" ...

```

- The dataset `data.fraction2` is the fraction subtraction data set with 536 students and 11 items. For this data set, several  $Q$  matrices are available. The data is a list. The first entry data contains the data frame. The entry `q.matrix1` contains the  $Q$ -matrix of Henson, Templin and Willse (2009). The third entry `q.matrix2` is an alternative  $Q$ -matrix of de la Torre (2009). The fourth entry is a modified  $Q$ -matrix of `q.matrix1`.

The format is:

```

$data : 'data.frame' :
..$ H01: int [1:536] 1 1 1 1 1 0 0 1 0 0 ...
..$ H02: int [1:536] 1 1 1 0 0 0 0 0 0 0 ...
..$ H03: int [1:536] 0 1 0 0 0 1 1 0 1 1 ...
..$ H04: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
..$ H05: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
..$ H06: int [1:536] 1 1 0 1 1 0 0 0 1 1 ...
..$ H08: int [1:536] 1 1 1 0 0 0 0 0 0 0 ...
..$ H09: int [1:536] 1 1 1 1 0 0 0 0 0 0 ...
..$ H10: int [1:536] 0 1 0 0 0 0 0 0 0 0 ...
..$ H11: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
..$ H13: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
$q.matrix1: int [1:11, 1:3] 1 1 1 1 1 1 1 1 1 1 ...
.- attr(*, "dimnames")=List of 2
...$: chr [1:11] "H01" "H02" "H03" "H04" ...
...$: chr [1:3] "QH1" "QH2" "QH3"
$q.matrix2: int [1:11, 1:5] 1 1 0 1 1 1 1 1 1 1 ...
.- attr(*, "dimnames")=List of 2
...$: chr [1:11] "H01" "H02" "H03" "H04" ...
...$: chr [1:5] "QT1" "QT2" "QT3" "QT4" ...
$q.matrix3: num [1:11, 1:3] 0 0 0 1 0 0 0 0 1 1 ...
.- attr(*, "dimnames")=List of 2
...$: chr [1:11] "H01" "H02" "H03" "H04" ...
...$: chr [1:3] "Dim1" "Dim2" "Dim3"

```

- The dataset `data.fraction3` contains 12 items and was used in de la Torre (2011).

```

List of 2
$data : 'data.frame': 536 obs. of 12 variables:
 ..$ B01: int [1:536] 0 1 1 1 0 0 0 0 0 0 ...
 ..$ B02: int [1:536] 1 1 1 1 1 0 0 1 0 0 ...
 ..$ B03: int [1:536] 0 1 1 1 1 1 0 0 0 0 ...
 ..$ B04: int [1:536] 0 1 0 0 0 1 1 0 1 1 ...
 ..$ B05: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
 ..$ B06: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
 ..$ B07: int [1:536] 1 1 0 1 1 0 0 0 1 1 ...
 ..$ B08: int [1:536] 1 1 1 1 0 1 0 0 1 0 ...
 ..$ B09: int [1:536] 1 1 1 1 0 0 0 0 0 0 ...
 ..$ B10: int [1:536] 0 1 0 0 0 0 0 0 0 0 ...
 ..$ B11: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
 ..$ B12: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
 $q.matrix: 'data.frame': 12 obs. of 5 variables:
 ..$ item: Factor w/ 13 levels "", "B01", "B02", ...: 2 3 4 5 6 7 8 9 10 11 ...
 ..$ QA1 : int [1:12] 1 1 1 1 1 1 1 1 1 1 ...
 ..$ QA2 : int [1:12] 0 1 0 0 1 1 1 0 0 0 ...
 ..$ QA3 : int [1:12] 0 1 0 1 1 1 0 1 1 1 ...
 ..$ QA4 : int [1:12] 0 1 0 0 1 1 0 0 0 1 ...

```

- The dataset `data.fraction4` contains 17 items and was used in de la Torre and Douglas (2004) and Chen, Liu, Xu and Ying (2015).

```

List of 2
$data : 'data.frame': 536 obs. of 17 variables:
 ..$ A01: int [1:536] 0 0 0 1 0 0 0 0 0 0 ...
 ..$ A02: int [1:536] 0 1 1 1 0 0 0 0 0 0 ...
 ..$ A03: int [1:536] 0 1 1 1 0 0 0 0 0 0 ...
 ..$ A04: int [1:536] 1 1 1 1 1 0 0 1 0 0 ...
 ..$ A05: int [1:536] 1 1 0 1 1 0 0 0 1 1 ...
 ..$ A06: int [1:536] 1 1 1 1 0 1 0 0 1 0 ...
 ..$ A07: int [1:536] 1 1 1 1 0 0 0 0 0 0 ...
 ..$ A08: int [1:536] 0 0 0 1 0 0 0 0 0 1 ...
 ..$ A09: int [1:536] 1 1 1 0 0 0 0 0 0 0 ...
 ..$ A10: int [1:536] 1 1 1 0 0 0 0 0 0 0 ...
 ..$ A11: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
 ..$ A12: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
 ..$ A13: int [1:536] 0 1 0 0 0 0 0 0 0 0 ...
 ..$ A14: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
 ..$ A15: int [1:536] 1 1 0 0 0 0 0 0 0 0 ...
 ..$ A16: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
 ..$ A17: int [1:536] 0 1 0 0 0 0 0 0 0 0 ...
 $q.matrix: 'data.frame': 17 obs. of 9 variables:
 ..$ item: Factor w/ 18 levels "", "A01", "A02", ...: 2 3 4 5 6 7 8 9 10 11 ...
 ..$ QA1 : int [1:17] 0 0 0 0 0 0 0 0 1 0 ...
 ..$ QA2 : int [1:17] 0 0 0 1 0 1 1 1 1 1 ...
 ..$ QA3 : int [1:17] 0 0 0 1 0 0 0 0 0 0 ...
 ..$ QA4 : int [1:17] 1 1 1 0 0 0 0 1 0 0 ...

```

```

..$ QA5 : int [1:17] 0 0 0 1 0 0 1 0 0 1 ...
..$ QA6 : int [1:17] 1 0 0 0 0 0 1 0 0 0 ...
..$ QA7 : int [1:17] 1 1 1 1 1 1 1 1 1 1 ...
..$ QA8 : int [1:17] 0 0 0 0 1 0 0 1 0 0 ...

```

- The dataset `data.fraction5` contains 15 items and was used as an example for the multiple strategy DINA model in de la Torre and Douglas (2008) and Hou and de la Torre (2014). The two Q-matrices for coding the multiple strategies are contained in one matrix `q.matrix` by joining the columns of both matrices.

List of 2

\$ data : 'data.frame': 536 obs. of 15 variables:

```

..$ T01: int [1:536] 0 1 1 1 0 0 0 0 0 0 ...
..$ T02: int [1:536] 1 1 1 1 1 0 0 1 0 0 ...
..$ T03: int [1:536] 0 1 1 1 1 1 0 0 0 0 ...
..$ T04: int [1:536] 1 1 1 0 0 0 0 0 0 0 ...
..$ T05: int [1:536] 0 1 0 0 0 1 1 0 1 1 ...
..$ T06: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
..$ T07: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
..$ T08: int [1:536] 1 1 0 1 1 0 0 0 1 1 ...
..$ T09: int [1:536] 1 1 1 1 0 1 0 0 1 0 ...
..$ T10: int [1:536] 1 1 1 0 0 0 0 0 0 0 ...
..$ T11: int [1:536] 1 1 1 1 0 0 0 0 0 0 ...
..$ T12: int [1:536] 0 1 0 0 0 0 0 0 0 0 ...
..$ T13: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...
..$ T14: int [1:536] 1 1 0 0 0 0 0 0 0 0 ...
..$ T15: int [1:536] 1 1 0 1 0 0 0 0 0 0 ...

```

\$ q.matrix: 'data.frame': 15 obs. of 15 variables:

```

..$ item: Factor w/ 16 levels "", "T01", "T02", ...: 2 3 4 5 6 7 8 9 10 11 ...
..$ SA1 : int [1:15] 0 1 1 1 0 1 1 1 1 1 ...
..$ SA2 : int [1:15] 0 1 0 1 0 1 1 1 0 0 ...
..$ SA3 : int [1:15] 0 1 0 1 1 1 1 0 1 1 ...
..$ SA4 : int [1:15] 0 1 0 1 0 1 1 0 0 1 ...
..$ SA5 : int [1:15] 0 0 0 1 0 0 0 0 0 1 ...
..$ SA6 : int [1:15] 0 0 0 0 0 0 0 0 0 0 ...
..$ SA7 : int [1:15] 0 0 0 0 0 0 0 0 0 0 ...
..$ SB1 : int [1:15] 0 1 1 1 0 1 1 1 1 1 ...
..$ SB2 : int [1:15] 0 0 0 0 1 1 1 1 0 1 ...
..$ SB3 : int [1:15] 0 0 0 0 0 0 0 0 0 0 ...
..$ SB4 : int [1:15] 0 0 0 0 0 0 0 0 0 0 ...
..$ SB5 : int [1:15] 0 0 0 1 1 0 0 0 0 1 ...
..$ SB6 : int [1:15] 0 1 0 1 1 1 1 0 1 0 ...
..$ SB7 : int [1:15] 0 0 0 0 1 0 0 0 0 0 ...

```

## Source

See [fraction.subtraction.data](#) for more information about the data source.

## References

- Chen, Y., Liu, J., Xu, G. and Ying, Z. (2015). Statistical analysis of Q-matrix based diagnostic classification models. *Journal of the American Statistical Association*, 110(510), 850-866.
- de la Torre, J. (2009). DINA model parameter estimation: A didactic. *Journal of Educational and Behavioral Statistics*, 34, 115-130.
- de la Torre, J. (2011). The generalized DINA model framework. *Psychometrika*, 76, 179-199.
- de la Torre, J., & Douglas, J. A. (2004). Higher-order latent trait models for cognitive diagnosis. *Psychometrika*, 69, 333-353.
- de la Torre, J., & Douglas, J. A. (2008). Model evaluation and multiple strategies in cognitive diagnosis: An analysis of fraction subtraction data. *Psychometrika*, 73, 595-624.
- Henson, R. A., Templin, J. T., & Willse, J. T. (2009). Defining a family of cognitive diagnosis models using log-linear models with latent variables. *Psychometrika*, 74, 191-210.
- Huo, Y., & de la Torre, J. (2014). Estimating a cognitive diagnostic model for multiple strategies via the EM algorithm. *Applied Psychological Measurement*, 38, 464-485.

## See Also

[GDINA: :frac20](#)

---

data.hr

*Dataset data.hr (Ravand et al., 2013)*

---

## Description

Dataset data.hr used for illustrating some functionalities of the **CDM** package (Ravand, Barati, & Widhiarso, 2013).

## Usage

```
data(data.hr)
```

## Format

The format of the dataset is:

```
List of 2
 $ data : num [1:1550, 1:35] 1 0 1 1 1 0 1 1 1 0 ...
 $ q.matrix: 'data.frame':
 ..$ Skill11: int [1:35] 0 0 0 0 0 0 1 0 0 0 ...
 ..$ Skill12: int [1:35] 0 0 0 0 1 0 0 0 0 0 ...
 ..$ Skill13: int [1:35] 0 1 1 1 1 0 0 1 0 0 ...
 ..$ Skill14: int [1:35] 1 0 0 0 0 0 0 0 1 1 ...
 ..$ Skill15: int [1:35] 0 0 0 0 0 1 0 0 1 1 ...
```

## Source

Simulated data according to Ravand et al. (2013).

## References

Ravand, H., Barati, H., & Widhiarso, W. (2013). Exploring diagnostic capacity of a high stakes reading comprehension test: A pedagogical demonstration. *Iranian Journal of Language Testing*, 3(1), 1-27.

## Examples

```
## Not run:
data(data.hr, package="CDM")

dat <- data.hr$data
Q <- data.hr$q.matrix

#####
# Model 1: DINA model
mod1 <- CDM::din( dat, q.matrix=Q )
summary(mod1)      # summary

# plot results
plot(mod1)

# inspect coefficients
coef(mod1)

# posterior distribution
posterior <- mod1$posterior
round( posterior[ 1:5, ], 4 ) # first 5 entries

# estimate class probabilities
mod1$attribute.patt

# individual classifications
mod1$pattern[1:5,] # first 5 entries

#####
# Model 2: GDINA model
mod2 <- CDM::gdina( dat, q.matrix=Q)
summary(mod2)

#####
# Model 3: Reduced RUM model
mod3 <- CDM::gdina( dat, q.matrix=Q, rule="RRUM" )
summary(mod3)

#-----
# model comparisons

# DINA vs GDINA
```

```

anova( mod1, mod2 )
##      Model  loglike Deviance Npars      AIC      BIC    Chisq df  p
##    1 Model 1 -31391.27 62782.54   101 62984.54 63524.49 195.9099 20 0
##    2 Model 2 -31293.32 62586.63   121 62828.63 63475.50      NA NA NA

# RRUM vs. GDINA
anova( mod2, mod3 )
##      Model  loglike Deviance Npars      AIC      BIC    Chisq df  p
##    2 Model 2 -31356.22 62712.43   105 62922.43 63483.76 125.7924 16 0
##    1 Model 1 -31293.32 62586.64   121 62828.64 63475.50      NA NA NA

# DINA vs. RRUM
anova(mod1,mod3)
##      Model  loglike Deviance Npars      AIC      BIC    Chisq df  p
##    1 Model 1 -31391.27 62782.54   101 62984.54 63524.49 70.11246  4 0
##    2 Model 2 -31356.22 62712.43   105 62922.43 63483.76      NA NA NA

#-----
# model fit

# DINA
fmod1 <- CDM::modelfit.cor.din( mod1, jkunits=0)
summary(fmod1)
## Test of Global Model Fit
##      type  value  p
##    1 max(X2) 16.35495 0.03125
##    2 abs(fcor) 0.10341 0.01416
##
## Fit Statistics
##              est
## MADcor      0.01911
## SRMSR       0.02445
## MX2         0.93157
## 100*MADRESIDCOV 0.39100
## MADQ3      0.02373

# GDINA
fmod2 <- CDM::modelfit.cor.din( mod2, jkunits=0)
summary(fmod2)
## Test of Global Model Fit
##      type  value p
##    1 max(X2) 7.73670 1
##    2 abs(fcor) 0.07215 1
##
## Fit Statistics
##              est
## MADcor      0.01830
## SRMSR       0.02300
## MX2         0.82584
## 100*MADRESIDCOV 0.37390
## MADQ3      0.02383

# RRUM

```



```
fmod3 <- CDM::modelfit.cor.din( mod3, jkunits=0)
summary(fmod3)
## Test of Global Model Fit
##      type      value      p
## 1  max(X2) 15.49369 0.04925
## 2 abs(fcor) 0.10076 0.02201
##
## Fit Statistics
##
##           est
## MADcor      0.01868
## SRMSR        0.02374
## MX2          0.87999
## 100*MADRESIDCOV 0.38409
## MADQ3        0.02416

## End(Not run)
```

---

data.jang

*Dataset Jang (2009)*


---

## Description

Simulated dataset according to the Jang (2005) L2 reading comprehension study.

## Usage

```
data(data.jang)
```

## Format

The format is:

```
List of 2
 $ data : num [1:1500, 1:37] 1 1 1 1 1 1 1 1 1 1 ...
 ..- attr(*, "dimnames")=List of 2
 .. ..$ : NULL
 .. ..$ : chr [1:37] "I1" "I2" "I3" "I4" ...
 $ q.matrix: 'data.frame':
 ..$ CDV: int [1:37] 1 0 0 1 0 0 0 0 0 0 ...
 ..$ CIV: int [1:37] 0 0 1 0 0 0 1 0 1 1 ...
 ..$ SSL: int [1:37] 1 1 1 1 0 0 0 0 0 0 ...
 ..$ TEI: int [1:37] 0 0 0 0 0 0 0 1 0 0 ...
 ..$ TIM: int [1:37] 0 0 0 1 1 1 0 0 0 0 ...
 ..$ INF: int [1:37] 0 1 0 0 0 0 1 0 0 0 ...
 ..$ NEG: int [1:37] 0 0 0 0 1 0 1 0 0 0 ...
 ..$ SUM: int [1:37] 0 0 0 0 1 0 0 0 0 0 ...
 ..$ MCF: int [1:37] 0 0 0 0 0 0 0 0 0 0 ...
```

## Source

Simulated dataset.

## References

Jang, E. E. (2009). Cognitive diagnostic assessment of L2 reading comprehension ability: Validity arguments for Fusion Model application to LanguEdge assessment. *Language Testing*, 26, 31-73.

## Examples

```
## Not run:
data(data.jang, package="CDM")

data <- data.jang$data
q.matrix <- data.jang$q.matrix

#### Model 1: Reduced RUM model
mod1 <- CDM::gdina( data, q.matrix, rule="RRUM", conv.crit=.001, increment.factor=1.025 )
summary(mod1)

#### Model 2: Additive model (identity link)
mod2 <- CDM::gdina( data, q.matrix, rule="ACDM", conv.crit=.001, linkfct="identity" )
summary(mod2)

#### Model 3: DINA model
mod3 <- CDM::gdina( data, q.matrix, rule="DINA", conv.crit=.001 )
summary(mod3)

anova(mod1,mod2)
##      Model  loglike Deviance Npars      AIC      BIC  Chisq df  p
##  1 Model 1 -30315.03 60630.06   153 60936.06 61748.98 88.29627  0  0
##  2 Model 2 -30270.88 60541.76   153 60847.76 61660.68      NA NA NA
anova(mod1,mod3)
##      Model  loglike Deviance Npars      AIC      BIC  Chisq df  p
##  2 Model 2 -30373.99 60747.97   129 61005.97 61691.38 117.9128 24  0
##  1 Model 1 -30315.03 60630.06   153 60936.06 61748.98      NA NA NA

# RRUM
summary( CDM::modelfit.cor.din( mod1, jkunits=0 ) )
##      type  value      p
##  1 max(X2) 11.79073 0.39645
##  2 abs(fcor) 0.09541 0.07422
##
##      est
##  MADcor      0.01834
##  SRMSR      0.02300
##  MX2        0.86718
##  100*MADRESIDCOV 0.38690
##  MADQ3      0.02413

# additive model (identity)
summary( CDM::modelfit.cor.din( mod2, jkunits=0 ) )
##      type  value      p
```

```

## 1  max(X2) 9.78958 1.00000
## 2  abs(fcor) 0.08770 0.22993
##                                     est
##  MADcor      0.01721
##  SRMSR      0.02158
##  MX2        0.69163
##  100*MADRESIDCOV 0.36343
##  MADQ3      0.02423

# DINA model
summary( CDM::modelfit.cor.din( mod3, jkunits=0) )
##          type      value      p
## 1  max(X2) 13.48449 0.16020
## 2  abs(fcor) 0.10651 0.01256
##                                     est
##  MADcor      0.01999
##  SRMSR      0.02495
##  MX2        0.92820
##  100*MADRESIDCOV 0.42226
##  MADQ3      0.02258

## End(Not run)

```

---

data.melab

*MELAB Data (Li, 2011)*


---

## Description

This is a simulated dataset according to the MELAB reading study (Li, 2011; Li & Suen, 2013). Li (2011) investigated the Fusion model (RUM model) for calibrating this dataset. The dataset in this package is simulated assuming the reduced RUM model (RRUM).

## Usage

```
data(data.melab)
```

## Format

The format of the dataset is:

```

List of 3
 $ data : num [1:2019, 1:20] 0 1 0 1 1 0 0 0 1 1 ...
 ..- attr(*, "dimnames")=List of 2
 ... ..$ : NULL
 ... ..$ : chr [1:20] "I1" "I2" "I3" "I4" ...
 $ q.matrix : 'data.frame':
 ..$ skill1: int [1:20] 1 1 0 0 1 1 0 1 0 1 ...
 ..$ skill2: int [1:20] 0 0 0 0 0 0 0 0 0 0 ...
 ..$ skill3: int [1:20] 0 0 0 1 0 1 1 0 1 0 ...
 ..$ skill4: int [1:20] 1 0 1 0 1 0 0 1 0 1 ...

```

```
$ skill.labels: 'data.frame':
..$ skill : Factor w/ 4 levels "skill1","skill2",...: 1 2 3 4
..$ skill.label: Factor w/ 4 levels "connecting and synthesizing",...: 4 3 2 1
```

## Source

Simulated data according to Li (2011).

## References

- Li, H. (2011). A cognitive diagnostic analysis of the MELAB reading test. *Spain Fellow*, 9, 17-46.
- Li, H., & Suen, H. K. (2013). Constructing and validating a Q-matrix for cognitive diagnostic analyses of a reading test. *Educational Assessment*, 18, 1-25.

## Examples

```
## Not run:
data(data.melab, package="CDM")

data <- data.melab$data
q.matrix <- data.melab$q.matrix

#### Model 1: Reduced RUM model
mod1 <- CDM::gdina( data, q.matrix, rule="RRUM" )
summary(mod1)

#### Model 2: GDINA model
mod2 <- CDM::gdina( data, q.matrix, rule="GDINA" )
summary(mod2)

#### Model 3: DINA model
mod3 <- CDM::gdina( data, q.matrix, rule="DINA" )
summary(mod3)

#### Model 4: 2PL model
mod4 <- CDM::gdm( data, theta.k=seq(-6,6,len=21), center )
summary(mod4)

#----
# Model comparisons

#### RRUM vs. GDINA
anova(mod1,mod2)
##      Model  loglike Deviance Npars      AIC      BIC  Chisq df      p
##  1 Model 1 -20252.74 40505.48    69 40643.48 41030.60 30.88801 18 0.02966
##  2 Model 2 -20237.30 40474.59    87 40648.59 41136.69      NA NA      NA

## -> GDINA is not superior to RRUM (according to AIC and BIC)

#### DINA vs. RRUM
anova(mod1,mod3)
```

```

##      Model  loglike Deviance Npars      AIC      BIC  Chisq df  p
##  2 Model 2 -20332.52 40665.04   55 40775.04 41083.61 159.5566 14 0
##  1 Model 1 -20252.74 40505.48   69 40643.48 41030.60      NA NA NA

## -> RRUM fits the data significantly better than the DINA model

*** RRUM vs. 2PL (use only AIC and BIC for comparison)
anova(mod1,mod4)
##      Model  loglike Deviance Npars      AIC      BIC  Chisq df  p
##  2 Model 2 -20390.19 40780.38   43 40866.38 41107.62 274.8962 26 0
##  1 Model 1 -20252.74 40505.48   69 40643.48 41030.60      NA NA NA

## -> RRUM fits the data better than 2PL

#----
# Model fit statistics

# RRUM
fmod1 <- CDM::modelfit.cor.din( mod1, jkunits=0)
summary(fmod1)
## Test of Global Model Fit
##      type  value  p
##  1 max(X2) 10.10408 0.28109
##  2 abs(fcor) 0.06726 0.24023
##
## Fit Statistics
##      est
## MADcor 0.01708
## SRMSR 0.02158
## MX2 0.96590
## 100*MADRESIDCOV 0.27269
## MADQ3 0.02781

## -> not a significant misfit of the RRUM model

# GDINA
fmod2 <- CDM::modelfit.cor.din( mod2, jkunits=0)
summary(fmod2)
## Test of Global Model Fit
##      type  value  p
##  1 max(X2) 10.40294 0.23905
##  2 abs(fcor) 0.06817 0.20964
##
## Fit Statistics
##      est
## MADcor 0.01703
## SRMSR 0.02151
## MX2 0.94468
## 100*MADRESIDCOV 0.27105
## MADQ3 0.02713

## End(Not run)

```

data.mg

*Large-Scale Dataset with Multiple Groups***Description**

Large-scale dataset with multiple groups, survey weights and 11 polytomous items.

**Usage**

```
data(data.mg)
```

**Format**

A data frame with 38243 observations on the following 14 variables.

idstud Student identifier

group Group identifier

weight Survey weight

I1 Item 1

I2 Item 2

I3 Item 3

I4 Item 4

I5 Item 5

I6 Item 6

I7 Item 7

I8 Item 8

I9 Item 9

I10 Item 10

I11 Item 11

**Source**

Subsample of a large-scale dataset of 11 survey questions.

**Examples**

```
## Not run:
library(psych)
data(dat.mg, package="CDM")
psych::describe( data.mg )
##   > psych::describe(data.mg)
##           var      n      mean      sd      median      trimmed      mad      min      max
## idstud  1 38243 1039653.91 19309.80 1037899.00 1039927.73 30240.59 1007168.00 1069949.00
## group   2 38243      8.06      4.07      7.00      8.06      5.93      2.00      14.00
```

```
## weight  3 38243    28.76  19.25   31.88   27.92  19.12    0.79  191.89
## I1      4 37665     0.88   0.32    1.00    0.98   0.00    0.00   1.00
## I2      5 37639     0.93   0.25    1.00    1.00   0.00    0.00   1.00
## I3      6 37473     0.76   0.43    1.00    0.83   0.00    0.00   1.00
## I4      7 37687     1.88   0.39    2.00    2.00   0.00    0.00   2.00
## I5      8 37638     1.36   0.75    2.00    1.44   0.00    0.00   2.00
## I6      9 37587     1.05   0.82    1.00    1.06   1.48    0.00   2.00
## I7     10 37576     1.55   0.85    2.00    1.57   1.48    0.00   3.00
## I8     11 37044     0.45   0.50    0.00    0.44   0.00    0.00   1.00
## I9     12 37249     0.48   0.50    0.00    0.47   0.00    0.00   1.00
## I10    13 37318     0.63   0.48    1.00    0.66   0.00    0.00   1.00
## I11    14 37412     1.35   0.80    1.00    1.35   1.48    0.00   3.00
```

```
## End(Not run)
```

---

data.pgdina

*Dataset for Polytomous GDINA Model*

---

## Description

Dataset for the estimation of the polytomous GDINA model.

## Usage

```
data(data.pgdina)
```

## Format

The dataset is a list with the item response data and the Q-matrix. The format is:

```
List of 2
 $ dat : num [1:1000, 1:30] 1 1 1 1 1 0 1 1 1 1 ...
 ..- attr(*, "dimnames")=List of 2
 .. ..$: NULL
 .. ..$: chr [1:30] "I1" "I2" "I3" "I4" ...
 $ q.matrix: num [1:30, 1:5] 1 0 0 0 0 1 0 0 0 2 ...
```

## Details

The dataset was simulated by the following R code:

```
set.seed(89)
# define Q-matrix
Qmatrix <- matrix(c(1,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,0,
1,1,2,0,0,0,0,1,2,0,0,0,0,1,2,0,0,0,0,1,1,2,0,0,0,1,2,2,0,1,0,2,
1,0,0,1,1,0,2,2,0,0,2,1,0,1,0,0,2,2,1,2,0,0,0,0,0,2,0,0,0,0,0,2,
0,0,0,0,0,2,0,0,0,0,0,1,2,0,2,0,0,0,2,0,2,0,0,0,2,0,1,2,0,0,2,0,
0,2,0,0,1,1,0,0,1,1,0,1,1,1,0,1,1,1,0,0,0,1,0,1,1,1,0,1,0,1),
nrow=30, ncol=5, byrow=TRUE)
```

```

# define covariance matrix between attributes
Sigma<- matrix(c(1,.6,.6,.3,.3,.6,1,.6,.3,.3,.6,.6,1,
.3,.3,.3,.3,.3,1,.8,.3,.3,.3,.8,1), 5,5, byrow=TRUE )
# define thresholds for attributes
q1 <- c(-.5, .9) # attributes 1,...,4
q2 <- c(0) # attribute 5
# number of persons
N <- 1000
# simulate latent attributes
alpha1 <- mvrnorm(n=N, mu=rep(0,5), Sigma=Sigma)
alpha <- 0*alpha1
for (aa in 1:4){
alpha[ alpha1[,aa] > q1[1], aa ] <- 1
alpha[ alpha1[,aa] > q1[2], aa ] <- 2
}
aa <- 5 ; alpha[ alpha1[,aa] > q2[1], aa ] <- 1
# define item parameters
guess <- c(.07,.01,.34,.07,.11,.23,.27,.07,.08,.34,.19,.19,.25,.04,.34,
.03,.29,.05,.01,.17,.15,.35,.19,.16,.08,.18,.19,.07,.17,.34)
slip <- c(0,.11,.14,.09,.03,.09,.03,.1,.14,.07,.06,.19,.09,.19,.07,.08,
.16,.18,.16,.02,.11,.12,.16,.14,.18,.01,.18,.14,.05,.18)
# simulate item responses
I <- 30 # number of items
dat <- latresp <- matrix( 0, N, I, byrow=TRUE)
for (ii in 1:I){
# ii <- 2
# latent response matrix
latresp[,ii] <- 1*( rowMeans( alpha >=matrix( Qmatrix[ ii, ], nrow=N,
ncol=5, byrow=TRUE ) )==1 )
# response probability
prob <- ifelse( latresp[,ii]==1, 1-slip[ii], guess[ii] )
# simulate item responses
dat[,ii] <- 1 * ( runif(N) < prob )
}
colnames(dat) <- paste0("I",1:I)

```

## References

Chen, J., & de la Torre, J. (2013). A general cognitive diagnosis model for expert-defined polytomous attributes. *Applied Psychological Measurement*, 37, 419-437.



## Description

This is a sub-dataset of the PISA 2000 of German students including 26 items of the reading test. The 26 items was analyzed in Chen and de la Torre (2014) and a subset of 20 items was analyzed in Chen and Chen (2016).

## Usage

```
data(data.pisa00R.ct)
data(data.pisa00R.cc)
```

## Format

- The format of the dataset `data.pisa00R.ct` (Chen & de la Torre, 2014) is:
 

```
List of 3
 $ data : 'data.frame': 1095 obs. of 111 variables:
 .. [list output truncated]
 $ q.matrix: num [1:26, 1:8] 0 1 0 0 0 1 0 0 0 1 ...
 ..- attr(*, "dimnames")=List of 2
 $ skills : chr [1:8] "Locating information" ...
```
- The format of the dataset `data.pisa00R.cc` (Q-matrix in Chen and Chen, 2016)
 

```
List of 2
 $ q.matrix: 'data.frame': 20 obs. of 5 variables:
 ..$ A1: num [1:20] 1 1 0 0 1 1 1 0 0 0 ...
 ..$ A2: num [1:20] 0 0 0 1 0 1 1 1 1 1 ...
 ..$ A3: num [1:20] 1 1 0 1 1 0 1 0 1 0 ...
 ..$ A4: num [1:20] 0 1 1 1 0 0 0 0 0 0 ...
 ..$ A5: num [1:20] 0 0 1 0 0 0 0 1 0 1 ...
 $ skills : Named chr [1:5] "Identifying Explicit Information" ...
 ..- attr(*, "names")=chr [1:5] "A1" "A2" "A3" "A4" ...
```

## References

Chen, H., & Chen, J. (2016). Exploring reading comprehension skill relationships through the G-DINA model. *Educational Psychology*, 36(6), 1049-1064.

Chen, J., & de la Torre, J. (2014). A procedure for diagnostically modeling extant large-scale assessment data: the case of the programme for international student assessment in reading. *Psychology*, 5(18), 1967-1978.

## Examples

```
#####
# EXAMPLE 1: PISA items from Chen and de la Torre (2014)
#           dichotomize item responses
#####

data(data.pisa00R.ct, package="CDM")
```

```

dat <- data.pisa00R.ct$data
Q <- data.pisa00R.ct$q.matrix
resp <- dat[, rownames(Q)]

*** extract item-wise maximum
maxK <- apply( resp, 2, max, na.rm=TRUE )
*** dichotomize response data
resp1 <- resp
for (ii in seq(1,ncol(resp)) ){
  resp1[,ii] <- 1 * ( resp[,ii]==maxK[ii] )
}

```

---

data.sda6

*Dataset SDA6 (Jurich & Bradshaw, 2014)*


---

### Description

This is a simulated dataset of the SDA6 study according to informations given in Jurich and Bradshaw (2014).

### Usage

```
data(data.sda6)
```

### Format

The datasets contains 17 items observed at 1710 students.

The format is:

List of 2

```
$ data : num [1:1710, 1:17] 0 1 0 1 0 0 0 0 1 0 ...
```

```
..- attr(*, "dimnames")=List of 2
```

```
.. ..$: NULL
```

```
.. ..$: chr [1:17] "MCM01" "MCM03" "MCM13" "MCM17" ...
```

```
$ q.matrix: 'data.frame':
```

```
..$ CM: int [1:17] 1 1 1 1 0 0 0 0 0 0 ...
```

```
..$ II: int [1:17] 0 0 0 0 1 1 1 1 0 0 ...
```

```
..$ PP: int [1:17] 0 0 0 0 0 0 0 0 1 1 ...
```

```
..$ DG: int [1:17] 0 0 0 0 0 0 0 0 0 0 ...
```

The meaning of the skills is

CM – Critique Methods

II – Identify Improvements

PP – Protect Participants

DG – Discern Generalizability

**Source**

Simulated data

**References**

Jurich, D. P., & Bradshaw, L. P. (2014). An illustration of diagnostic classification modeling in student learning outcomes assessment. *International Journal of Testing, 14*, 49-72.

**Examples**

```
## Not run:
data(data.sda6, package="CDM")

data <- data.sda6$data
q.matrix <- data.sda6$q.matrix

#### Model 1a: LCDM with gdina
mod1a <- CDM::gdina( data, q.matrix, rule="ACDM", linkfct="logit",
                    reduced.skillspace=FALSE )
summary(mod1a)

#### Model 1b: estimate LCDM with gdm
mod1b <- CDM::gdm( data, q.matrix=q.matrix, theta.k=c(0,1) )
summary(mod1b)

#### Model 2: LCDM with hierarchy II > CM
B <- "II > CM"
ss2 <- CDM::skillspace.hierarchy(B=B, skill.names=colnames(q.matrix) )
mod2 <- CDM::gdina( data, q.matrix, rule="ACDM", linkfct="logit",
                   skillclasses=ss2$skillspace.reduced,
                   reduced.skillspace=FALSE )
summary(mod2)

#### Model 3: LCDM with hierarchy II > CM and DG > CM
B <- "II > CM
      DG > CM"
ss2 <- CDM::skillspace.hierarchy(B=B, skill.names=colnames(q.matrix) )
mod3 <- CDM::gdina( data, q.matrix, rule="ACDM", linkfct="logit",
                   skillclasses=ss2$skillspace.reduced,
                   reduced.skillspace=FALSE )
summary(mod3)

# model comparisons
anova(mod1a,mod2)
anova(mod1a,mod3)
# model fit
summary( CDM::modelfit.cor.din(mod1a))
summary( CDM::modelfit.cor.din(mod2) )
summary( CDM::modelfit.cor.din(mod3) )

## End(Not run)
```

---

data.Students

*Dataset Student Questionnaire*

---

### Description

This dataset contains item responses of students at a scale of cultural activities (act), mathematics self concept (sc) and mathematics joyment (mj).

### Usage

```
data(data.Students)
```

### Format

A data frame with 2400 observations on the following 15 variables.

urban Urbanization level: 1=town, 0=otherwise

female A dummy variable for female student

act1 Visit a museum (0=never, 1=once or twice a year, 2=more than twice a year)

act2 Visit a theater or classical concert (0,1,2)

act3 Visit a rock or pop concert (0,1,2)

act4 Visit a cinema (0,1,2)

act5 Visit a public library (0,1,2)

sc1 Item 1 self concept "I am usually good at math." (0=do not agree at all, 1=rather do not agree, 2=rather agree, 3=completely agree)

sc2 Item 2 self concept: "Mathematics is harder for me than many of my classmates." (0,1,2,3) (reversed)

sc3 Item 3 self concept: "I am just not good at math." (0,1,2,3) (reversed)

sc4 Item 4 self concept: "I'm learning fast in math." (0,1,2,3)

mj1 Item 1 mathematics joyment: "I would like more math at school." (0,1,2,3)

mj2 Item 2 mathematics joyment: "I like to learn mathematics." (0,1,2,3)

mj3 Item 3 mathematics joyment: "Math is boring." (0,1,2,3) (reversed)

mj4 Item 4 mathematics joyment: "I like math." (0,1,2,3)

### Source

Subsample of students from an Austrian survey of 8th grade students.

**Examples**

```
## Not run:
library(psych)
data(data.Students, package="CDM")
psych::describe(data.Students)
##          var      n mean  sd median trimmed  mad min max range  skew kurtosis  se
## urban    1 2400 0.31 0.46   0.0   0.27 0.00   0  1  1  0.81   -1.34 0.01
## female   2 2400 0.51 0.50   1.0   0.51 0.00   0  1  1 -0.03   -2.00 0.01
## act1     3 2248 0.65 0.73   0.5   0.56 0.74   0  2  2  0.64   -0.88 0.02
## act2     4 2230 0.47 0.69   0.0   0.34 0.00   0  2  2  1.13   -0.06 0.01
## act3     5 2218 0.33 0.60   0.0   0.21 0.00   0  2  2  1.62    1.48 0.01
## act4     6 2342 1.35 0.76   2.0   1.44 0.00   0  2  2 -0.69   -0.96 0.02
## act5     7 2223 0.52 0.74   0.0   0.40 0.00   0  2  2  1.05   -0.41 0.02
## sc1      8 2352 0.96 0.80   1.0   0.91 1.48   0  3  3  0.45   -0.39 0.02
## sc2      9 2347 0.90 0.88   1.0   0.81 1.48   0  3  3  0.66   -0.41 0.02
## sc3     10 2335 0.86 0.96   1.0   0.73 1.48   0  3  3  0.84   -0.35 0.02
## sc4     11 2337 1.29 0.90   1.0   1.24 1.48   0  3  3  0.24   -0.71 0.02
## mj1     12 2351 2.26 0.82   2.0   2.37 1.48   0  3  3 -0.94    0.28 0.02
## mj2     13 2345 1.89 0.91   2.0   1.95 1.48   0  3  3 -0.35   -0.80 0.02
## mj3     14 2334 1.47 1.02   1.0   1.47 1.48   0  3  3  0.10   -1.11 0.02
## mj4     15 2346 1.59 0.99   2.0   1.62 1.48   0  3  3 -0.03   -1.06 0.02

## End(Not run)
```

---

data.timss03.G8.su      *TIMSS 2003 Mathematics 8th Grade (Su et al., 2013)*

---

**Description**

This is a dataset with a subset of 23 Mathematics items from TIMSS 2003 items used in Su, Choi, Lee, Choi and McAninch (2013).

**Usage**

```
data(data.timss03.G8.su)
```

**Format**

The data contains scored item responses (data), the Q-matrix (q.matrix) and further item information (iteminfo).

The format is

List of 3

```
$ data : 'data.frame':
..$ idstud : num [1:757] 1e+07 1e+07 1e+07 1e+07 1e+07 ...
..$ idbook : num [1:757] 1 1 1 1 1 1 1 1 1 1 ...
..$ M012001 : num [1:757] 0 1 0 0 1 0 1 0 0 0 ...
..$ M012002 : num [1:757] 1 1 0 1 0 0 1 1 1 1 ...
..$ M012004 : num [1:757] 0 1 1 1 1 0 1 1 0 0 ...
```

```
[...]
..$ M022234B: num [1:757] 0 0 0 0 0 0 0 0 0 0 ...
..$ M022251 : num [1:757] 0 0 0 0 0 0 0 0 0 0 ...
..$ M032570 : num [1:757] 1 1 0 1 0 0 1 1 1 1 ...
..$ M032643 : num [1:757] 1 0 0 0 0 0 1 1 0 0 ...
$q.matrix: int [1:23, 1:13] 1 0 0 0 0 0 1 0 0 0 ...
..- attr(*, "dimnames")=List of 2
...$: chr [1:23] "M012001" "M012002" "M012004" "M012016" ...
...$: chr [1:13] "S1" "S2" "S3" "S4" ...
$iteminfo: chr [1:23, 1:9] "M012001" "M012002" "M012004" "M012016" ...
..- attr(*, "dimnames")=List of 2
...$: NULL
...$: chr [1:9] "item" "ItemType" "reporting_category" "content" ...
```

For a detailed description of skills S1, S2, ..., S15 see Su et al. (2013, Table 2).

### Source

Subset of US 8th graders (Booklet 1) in the TIMSS 2003 mathematics study

### References

Skaggs, G., Wilkins, J. L. M., & Hein, S. F. (2016). Grain size and parameter recovery with TIMSS and the general diagnostic model. *International Journal of Testing*, 16(4), 310-330.

Su, Y.-L., Choi, K. M., Lee, W.-C., Choi, T., & McAninch, M. (2013). *Hierarchical cognitive diagnostic analysis for TIMSS 2003 mathematics*. CASMA Research Report 35. Center for Advanced Studies in Measurement and Assessment (CASMA), University of Iowa.

### See Also

The TIMSS 2003 dataset for 8th graders (with a larger number of items) was also analyzed in Skaggs, Wilkins and Hein (2016).

### Examples

```
## Not run:
#####
# EXAMPLE 1: Data Su et al. (2013)
#####

data(data.timss03.G8.su, package="CDM")
data <- data.timss03.G8.su$data[,-c(1,2)]
q.matrix <- data.timss03.G8.su$q.matrix

### Model 1: DINA model with complete skill space of 2^13=8192 skill classes
mod1 <- CDM::din( data, q.matrix )

### Model 2: Skill space approximation with 3000 skill classes instead of
# 2^13=8192 classes as in Model 1
ss2 <- CDM::skillspace.approximation( L=3000, K=ncol(q.matrix) )
```

```

mod2 <- CDM::din( data, q.matrix, skillclasses=ss2 )

#### Model 3: DINA model with a hierarchical skill space
# see Su et al. (2013): Fig. 6
B <- "S1 > S2 > S7 > S8
      S15 > S9
      S3 > S9
      S13 > S4 > S9
      S14 > S5 > S6 > S11"
# Note that S10 and S12 are not included in the dataset contained in this package
skill.names <- colnames(q.matrix)
ss3 <- CDM::skillspace.hierarchy(B=B, skill.names=skill.names)
# The reduced skill space "only" contains 325 skill classes
mod3 <- CDM::din( data, q.matrix, skillclasses=ss3$skillspace.reduced )

## End(Not run)

```

---

data.timss07.G4.lee     *TIMSS 2007 Mathematics 4th Grade (Lee et al., 2011)*

---

## Description

TIMSS 2007 (Grade 4) dataset with 25 mathematics (dichotomized) items used in Lee, Park and Taylan (2011), Park and Lee (2014) and Park, Xing and Lee (2018). The dataset includes a sample of 698 Austrian students.

## Usage

```

data(data.timss07.G4.lee)
data(data.timss07.G4.py)
data(data.timss07.G4.Qdomains)

```

## Format

- The dataset `data.timss07.G4.lee` is a list containing dichotomous item responses (`data`; information on booklet and gender included), the Q-matrix (`q.matrix`) and descriptions of the skills (`skillinfo`) used in Lee et al. (2011).

The format is:

List of 3

\$ data : 'data.frame':

..\$ idstud : int [1:698] 10110 10111 20105 20106 30203 30204 40106 40107 60111 60112

...

..\$ idbook : int [1:698] 4 5 4 5 4 5 4 5 4 5 ...

..\$ girl : int [1:698] 0 0 1 1 0 1 0 1 1 1 ...

..\$ M041052 : num [1:698] 1 NA 1 NA 0 NA 1 NA 1 NA ...

..\$ M041056 : num [1:698] 1 NA 0 NA 0 NA 0 NA 1 NA ...

..\$ M041069 : num [1:698] 0 NA 0 NA 0 NA 0 NA 1 NA ...

..\$ M041076 : num [1:698] 1 NA 0 NA 1 NA 1 NA 0 NA ...

```

..$ M041281 : num [1:698] 1 NA 0 NA 1 NA 1 NA 0 NA ...
..$ M041164 : num [1:698] 1 NA 1 NA 0 NA 1 NA 1 NA ...
..$ M041146 : num [1:698] 0 NA 0 NA 1 NA 1 NA 0 NA ...
..$ M041152 : num [1:698] 1 NA 1 NA 1 NA 0 NA 1 NA ...
..$ M041258A: num [1:698] 0 NA 1 NA 1 NA 0 NA 1 NA ...
..$ M041258B: num [1:698] 1 NA 0 NA 1 NA 0 NA 1 NA ...
..$ M041131 : num [1:698] 0 NA 0 NA 1 NA 1 NA 1 NA ...
..$ M041275 : num [1:698] 1 NA 0 NA 0 NA 1 NA 1 NA ...
..$ M041186 : num [1:698] 1 NA 0 NA 1 NA 1 NA 0 NA ...
..$ M041336 : num [1:698] 1 NA 1 NA 0 NA 1 NA 0 NA ...
..$ M031303 : num [1:698] 1 1 0 1 0 1 1 1 0 0 ...
..$ M031309 : num [1:698] 1 0 1 1 1 1 1 1 0 0 ...
..$ M031245 : num [1:698] 0 0 0 0 0 0 0 0 0 0 ...
..$ M031242A: num [1:698] 1 1 0 1 1 1 1 1 0 0 ...
..$ M031242B: num [1:698] 0 1 0 1 1 1 1 1 1 0 ...
..$ M031242C: num [1:698] 1 1 0 1 1 1 1 1 1 0 ...
..$ M031247 : num [1:698] 0 0 0 0 0 0 0 0 0 0 ...
..$ M031219 : num [1:698] 1 1 1 0 1 1 1 1 1 0 ...
..$ M031173 : num [1:698] 1 1 0 0 0 1 1 1 1 0 ...
..$ M031085 : num [1:698] 1 0 0 1 1 1 0 0 0 1 ...
..$ M031172 : num [1:698] 1 0 0 1 1 1 1 1 1 0 ...
$q.matrix : int [1:25, 1:15] 1 0 0 0 0 0 0 1 0 0 ...
.- attr(*, "dimnames")=List of 2
...$: chr [1:25] "M041052" "M041056" "M041069" "M041076" ...
...$: chr [1:15] "NWN01" "NWN02" "NWN03" "NWN04" ...
$skillinfo: 'data.frame':
..$ skillindex : int [1:15] 1 2 3 4 5 6 7 8 9 10 ...
..$ skill : Factor w/ 15 levels "DOR15", "DRI13",...: 12 13 14 15 8 9 10 11 4 6 ...
..$ content : Factor w/ 3 levels "D", "G", "N": 3 3 3 3 3 3 3 2 2 ...
..$ content_label : Factor w/ 3 levels "Data Display",...: 3 3 3 3 3 3 3 2 2 ...
..$ subcontent : Factor w/ 9 levels "FD", "LA", "LM",...: 9 9 9 9 1 1 4 6 2 8 ...
..$ subcontent_label: Factor w/ 9 levels "Fractions and Decimals",...: 9 9 9 9 1 1 4
6 2 8 ...

```

- The dataset data.timss07.G4.py uses the same items as data.timss07.G4.lee but employs a simplified Q-matrix with 7 skills. This Q-matrix was used in Park and Lee (2014) and Park et al. (2018).

```
List of 3
```

```
$q.matrix: 'data.frame': 25 obs. of 7 variables:
```

```

..$ N1: num [1:25] 1 0 1 1 1 0 0 1 0 0 ...
..$ N2: num [1:25] 0 1 1 1 0 0 0 0 0 0 ...
..$ N3: num [1:25] 0 0 0 0 1 0 0 0 0 0 ...
..$ G4: num [1:25] 0 0 0 0 0 0 1 0 0 1 ...
..$ G5: num [1:25] 0 0 0 0 0 1 1 1 1 1 ...
..$ G6: num [1:25] 0 0 0 0 0 1 1 0 0 0 ...
..$ D7: num [1:25] 0 0 0 0 0 0 0 0 0 0 ...

```

```
$domains : Named chr [1:3] "Number" "Geometric Shapes and Measures" "Data Display"
```

```
.- attr(*, "names")=chr [1:3] "N" "G" "D"
```



```
$ skills : Named chr [1:7] "Whole Numbers" ...
..- attr(*, "names")=chr [1:7] "N1" "N2" "N3" "G4" ...
```

- The Q-matrix data.timss07.G4.Qdomains is a simplification of data.timss07.G4.py\$q.matrix to 3 domains and involves a simple structure of skills.

```
num [1:25, 1:3] 1 1 1 1 1 0 0 1 0 0 ...
- attr(*, "dimnames")=List of 2
..$: chr [1:25] "M041052" "M041056" "M041069" "M041076" ...
..$: chr [1:3] "N" "G" "D"
```

## Source

TIMSS 2007 study, 4th Grade, Austrian sample on booklets 4 and 5

## References

Lee, Y. S., Park, Y. S., & Taylan, D. (2011). A cognitive diagnostic modeling of attribute mastery in Massachusetts, Minnesota, and the US national sample using the TIMSS 2007. *International Journal of Testing, 11*, 144-177.

Park, Y. S., & Lee, Y. S. (2014). An extension of the DINA model using covariates: Examining factors affecting response probability and latent classification. *Applied Psychological Measurement, 38*(5), 376-390.

Park, Y. S., Xing, K., & Lee, Y. S. (2018). Explanatory cognitive diagnostic models: Incorporating latent and observed predictors. *Applied Psychological Measurement, 42*(5), 376-392.

Yamaguchi, K., & Okada, K. (2018). Comparison among cognitive diagnostic models for the TIMSS 2007 fourth grade mathematics assessment. *PLoS ONE, 13*(2), e0188691.

## See Also

A comparison of several countries based on the 25 items is conducted in Yamaguchi and Okada (2018).

## Examples

```
## Not run:
#####
# EXAMPLE 1: DINA model Lee et al. (2011) - 15 skills
#####

data(data.timss07.G4.lee, package="CDM")
dat <- data.timss07.G4.lee$data
q.matrix <- data.timss07.G4.lee$q.matrix
# extract items
items <- grep( "M0", colnames(dat), value=TRUE )

#### Model 1: estimate DINA model
mod1 <- CDM::din( dat[,items], q.matrix )
summary(mod1)
```

```
#####
# EXAMPLE 2: DINA models Park and Lee (2014) - 7 skills and 3 skills
#####

data(data.timss07.G4.lee, package="CDM")
data(data.timss07.G4.py, package="CDM")
data(data.timss07.G4.Qdomains, package="CDM")

dat <- data.timss07.G4.lee$data
q.matrix <- data.timss07.G4.py$q.matrix
items <- rownames(q.matrix)

### Model 1: estimate DINA model
mod1 <- CDM::din( dat[,items], q.matrix )
summary(mod1)

### Model 2: estimate DINA model with Q-matrix defined by domains
Q <- data.timss07.G4.Qdomains
mod2 <- CDM::din( dat[,items], q.matrix=Q )
summary(mod2)

## End(Not run)
```

---

data.timss11.G4.AUT     *TIMSS 2011 Mathematics 4th Grade Austrian Students*

---

## Description

This is the TIMSS 2011 dataset of 4668 Austrian fourth-graders. See George and Robitzsch (2014, 2015, 2018) for publications using the TIMSS 2011 dataset for cognitive diagnosis modeling. The dataset has also been analyzed by Sedat and Arican (2015).

## Usage

```
data(data.timss11.G4.AUT)
data(data.timss11.G4.AUT.part)
data(data.timss11.G4.sa)
```

## Format

- The format of the dataset data.timss11.G4.AUT is:

```
List of 4
 $ data : 'data.frame':
 ..$ uidschool: int [1:4668] 10040001 10040001 10040001 10040001 10040001 10040001 10040001
 10040001 10040001 10040001 10040001 ...
 ..$ uidstud : num [1:4668] 1e+13 1e+13 1e+13 1e+13 1e+13 ...
 ..$ IDCNTRY : int [1:4668] 40 40 40 40 40 40 40 40 40 40 ...
 ..$ IDBOOK : int [1:4668] 10 12 13 14 1 2 3 4 5 6 ...
```

```

..$ IDSCHOOL : int [1:4668] 1 1 1 1 1 1 1 1 1 1 ...
..$ IDCLASS : int [1:4668] 102 102 102 102 102 102 102 102 102 102 ...
..$ IDSTUD : int [1:4668] 10201 10203 10204 10205 10206 10207 10208 10209 10210 10211
...
..$ TOTWGT : num [1:4668] 17.5 17.5 17.5 17.5 17.5 ...
..$ HOUWGT : num [1:4668] 1.04 1.04 1.04 1.04 1.04 ...
..$ SENWGT : num [1:4668] 0.111 0.111 0.111 0.111 0.111 ...
..$ SCHWGT : num [1:4668] 11.6 11.6 11.6 11.6 11.6 ...
..$ STOTWGTU : num [1:4668] 524 524 524 524 524 ...
..$ WGTADJ1 : int [1:4668] 1 1 1 1 1 1 1 1 1 1 ...
..$ WGTFAC1 : num [1:4668] 11.6 11.6 11.6 11.6 11.6 ...
..$ JKCREP : int [1:4668] 1 1 1 1 1 1 1 1 1 1 ...
..$ JKCZONE : int [1:4668] 1 1 1 1 1 1 1 1 1 1 ...
..$ female : int [1:4668] 1 0 1 1 1 1 1 1 0 0 ...
..$ M031346A : int [1:4668] NA NA NA 1 1 NA NA NA NA NA ...
..$ M031346B : int [1:4668] NA NA NA 0 0 NA NA NA NA NA ...
..$ M031346C : int [1:4668] NA NA NA 1 1 NA NA NA NA NA ...
..$ M031379 : int [1:4668] NA NA NA 0 0 NA NA NA NA NA ...
..$ M031380 : int [1:4668] NA NA NA 0 0 NA NA NA NA NA ...
..$ M031313 : int [1:4668] NA NA NA 1 1 NA NA NA NA NA ...
.. [list output truncated]
$q.matrix1:'data.frame':
..$ item : Factor w/ 174 levels "M031004", "M031009", ...: 29 30 31 32 33 25 8 5 17 163
...
..$ Co_DA: int [1:174] 0 0 0 0 0 0 0 0 0 0 ...
..$ Co_DK: int [1:174] 0 0 0 0 0 0 0 0 0 0 ...
..$ Co_DR: int [1:174] 0 0 0 0 0 0 0 0 0 0 ...
..$ Co_GA: int [1:174] 0 0 0 0 0 0 0 0 0 0 ...
..$ Co_GK: int [1:174] 0 0 0 0 0 0 1 1 0 0 ...
..$ Co_GR: int [1:174] 0 0 0 0 0 0 0 0 0 0 ...
..$ Co_NA: int [1:174] 1 0 0 0 0 1 0 0 0 1 ...
..$ Co_NK: int [1:174] 0 0 0 0 0 0 0 0 0 0 ...
..$ Co_NR: int [1:174] 0 1 1 1 1 0 0 0 1 0 ...
$q.matrix2:'data.frame':
..$ item : Factor w/ 174 levels "M031004", "M031009", ...: 29 30 31 32 33 25 8 5 17 163
...
..$ CONT_D: int [1:174] 0 0 0 0 0 0 0 0 0 0 ...
..$ CONT_G: int [1:174] 0 0 0 0 0 0 1 1 0 0 ...
..$ CONT_N: int [1:174] 1 1 1 1 1 1 0 0 1 1 ...
$q.matrix3:'data.frame': 174 obs. of 4 variables:
..$ item : Factor w/ 174 levels "M031004", "M031009", ...: 29 30 31 32 33 25 8 5 17 163
...
..$ COGN_A: int [1:174] 1 0 0 0 0 1 0 0 0 1 ...
..$ COGN_K: int [1:174] 0 0 0 0 0 0 1 1 0 0 ...
..$ COGN_R: int [1:174] 0 1 1 1 1 0 0 0 1 0 ...

```

- The dataset data.timss11.G4.AUT.part is a part of data.timss11.G4.AUT and contains only the first three booklets (with N=1010 students). The format is

```

List of 4
$data : 'data.frame': 1010 obs. of 109 variables:
..$ uidschool: int [1:1010] 10040001 10040001 10040001 10040001 ...
..$ uidstud : num [1:1010] 1e+13 1e+13 1e+13 1e+13 1e+13 ...
..$ IDCNTRY : int [1:1010] 40 40 40 40 40 40 40 40 40 40 ...
..$ IDBOOK : int [1:1010] 1 2 3 1 2 1 2 3 1 2 ...
..$ IDSCHOOL : int [1:1010] 1 1 1 1 1 2 2 2 3 3 ...
..$ IDCLASS : int [1:1010] 102 102 102 102 102 ...
..$ IDSTUD : int [1:1010] 10206 10207 10208 10220 ...
..$ TOTWGT : num [1:1010] 17.5 17.5 17.5 17.5 17.5 ...
..$ HOUWGT : num [1:1010] 1.04 1.04 1.04 1.04 1.04 ...
..$ SENWGT : num [1:1010] 0.111 0.111 0.111 0.111 0.111 ...
..$ SCHWGT : num [1:1010] 11.6 11.6 11.6 11.6 11.6 ...
..$ STOTWGTU : num [1:1010] 524 524 524 524 524 ...
..$ WGTADJ1 : int [1:1010] 1 1 1 1 1 1 1 1 1 ...
..$ WGTFAC1 : num [1:1010] 11.6 11.6 11.6 11.6 11.6 ...
..$ JKCREP : int [1:1010] 1 1 1 1 1 0 0 0 0 ...
..$ JKCZONE : int [1:1010] 1 1 1 1 1 1 1 2 2 ...
..$ female : int [1:1010] 1 1 1 1 0 1 1 1 1 ...
..$ M031346A : int [1:1010] 1 NA NA 1 NA 1 NA NA 1 NA ...
..$ M031346B : int [1:1010] 0 NA NA 1 NA 0 NA NA 0 NA ...
..$ M031346C : int [1:1010] 1 NA NA 0 NA 0 NA NA 0 NA ...
..$ M031379 : int [1:1010] 0 NA NA 0 NA 0 NA NA 1 NA ...
..$ M031380 : int [1:1010] 0 NA NA 0 NA 0 NA NA 0 NA ...
..$ M031313 : int [1:1010] 1 NA NA 0 NA 1 NA NA 0 NA ...
..$ M031083 : int [1:1010] 1 NA NA 1 NA 1 NA NA 1 NA ...
..$ M031071 : int [1:1010] 0 NA NA 0 NA 1 NA NA 0 NA ...
..$ M031185 : int [1:1010] 0 NA NA 1 NA 0 NA NA 0 NA ...
..$ M051305 : int [1:1010] 1 1 NA 1 0 0 0 NA 0 1 ...
..$ M051091 : int [1:1010] 1 1 NA 1 1 1 1 NA 1 0 ...
.. [list output truncated]
$q.matrix1: 'data.frame': 47 obs. of 10 variables:
..$ item : Factor w/ 174 levels "M031004", "M031009", ...: 29 30 31 32 33 25 8 5 17 163
...
..$ Co_DA: int [1:47] 0 0 0 0 0 0 0 0 0 ...
..$ Co_DK: int [1:47] 0 0 0 0 0 0 0 0 0 ...
..$ Co_DR: int [1:47] 0 0 0 0 0 0 0 0 0 ...
..$ Co_GA: int [1:47] 0 0 0 0 0 0 0 0 0 ...
..$ Co_GK: int [1:47] 0 0 0 0 0 0 1 1 0 ...
..$ Co_GR: int [1:47] 0 0 0 0 0 0 0 0 0 ...
..$ Co_NA: int [1:47] 1 0 0 0 0 1 0 0 0 ...
..$ Co_NK: int [1:47] 0 0 0 0 0 0 0 0 0 ...
..$ Co_NR: int [1:47] 0 1 1 1 1 0 0 0 1 ...
$q.matrix2: 'data.frame': 47 obs. of 4 variables:
..$ item : Factor w/ 174 levels "M031004", "M031009", ...: 29 30 31 32 33 25 8 5 17 163
...
..$ CONT_D: int [1:47] 0 0 0 0 0 0 0 0 0 ...
..$ CONT_G: int [1:47] 0 0 0 0 0 0 1 1 0 ...

```

```

..$ CONT_N: int [1:47] 1 1 1 1 1 1 0 0 1 1 ...
$q.matrix3: 'data.frame': 47 obs. of 4 variables:
..$ item : Factor w/ 174 levels "M031004", "M031009", ...: 29 30 31 32 33 25 8 5 17 163
...
..$ COGN_A: int [1:47] 1 0 0 0 0 1 0 0 0 1 ...
..$ COGN_K: int [1:47] 0 0 0 0 0 0 1 1 0 0 ...
..$ COGN_R: int [1:47] 0 1 1 1 1 0 0 0 1 0 ...

```

- The dataset `data.timss11.G4.sa` contains the Q-matrix used in Sedat and Arican (2015).

List of 2

```

$q.matrix: 'data.frame': 31 obs. of 13 variables:
..$ N1 : num [1:31] 1 0 0 1 1 0 0 0 0 0 ...
..$ N2 : num [1:31] 1 1 0 0 1 0 0 0 0 0 ...
..$ N3 : num [1:31] 0 0 0 0 1 0 0 0 0 0 ...
..$ A4 : num [1:31] 0 0 1 0 0 1 1 1 0 0 ...
..$ A5 : num [1:31] 0 0 0 0 0 1 0 1 0 0 ...
..$ A6 : num [1:31] 0 0 0 0 0 0 0 0 0 0 ...
..$ A7 : num [1:31] 0 0 1 0 0 0 0 0 0 0 ...
..$ G8 : num [1:31] 0 0 0 0 0 0 0 0 1 1 ...
..$ G9 : num [1:31] 0 0 0 0 0 0 0 0 1 1 ...
..$ G10: num [1:31] 0 0 0 0 0 0 0 0 1 1 ...
..$ G11: num [1:31] 0 0 0 0 0 1 0 0 0 0 ...
..$ D12: num [1:31] 0 0 0 0 0 0 0 0 0 0 ...
..$ D13: num [1:31] 0 0 0 0 0 0 0 0 0 0 ...
$ skills : Named chr [1:13] "Possesses understanding of" __truncated__ ...
..- attr(*, "names")=chr [1:13] "N1" "N2" "N3" "A4" ...

```

## References

- George, A. C., & Robitzsch, A. (2014). Multiple group cognitive diagnosis models, with an emphasis on differential item functioning. *Psychological Test and Assessment Modeling*, 56(4), 405-432.
- George, A. C., & Robitzsch, A. (2015) Cognitive diagnosis models in R: A didactic. *The Quantitative Methods for Psychology*, 11, 189-205.
- George, A. C., & Robitzsch, A. (2018). Focusing on interactions between content and cognition: A new perspective on gender differences in mathematical sub-competencies. *Applied Measurement in Education*, 31(1), 79-97.
- Sedat, S. E. N., & Arican, M. (2015). A diagnostic comparison of Turkish and Korean students' Mathematics performances on the TIMSS 2011 assessment. *Journal of Measurement and Evaluation in Education and Psychology*, 6(2), 238-253.

**Description**

Computes the variance of a nonlinear parameter using the delta method.

**Usage**

```
deltaMethod(derived.pars, est, Sigma, h=1e-05)
```

**Arguments**

derived.pars	Vector of derived parameters written in R formula framework (see Examples).
est	Vector of parameter estimates
Sigma	Covariance matrix of parameters
h	Numerical differentiation parameter

**Value**

coef	Vector of nonlinear parameters
vcov	Covariance matrix of nonlinear parameters
se	Vector of standard errors
A	First derivative of nonlinear transformation
univarTest	Data frame containing univariate summary of nonlinear parameters
WaldTest	Multivariate parameter test for nonlinear parameter

**See Also**

See `car::deltaMethod` or `msm::deltamethod`.

**Examples**

```
#####
# EXAMPLE 1: Nonlinear parameter
#####

#-- parameter estimate
est <- c( 510.67, 102.57)
names(est) <- c("mu", "sigma")
#-- covariance matrix
Sigma <- matrix( c(5.83, 0.45, 0.45, 3.21 ), nrow=2, ncol=2 )
colnames(Sigma) <- rownames(Sigma) <- names(est)
#-- define derived nonlinear parameters
derived.pars <- list( "d"=~ I( ( mu - 508 ) / sigma ),
                    "dsig"=~ I( sigma / 100 - 1 ) )

###* apply delta method
res <- CDM::deltaMethod( derived.pars, est, Sigma )
res
```

**Description**

din provides parameter estimation for cognitive diagnosis models of the types “DINA”, “DINO” and “mixed DINA and DINO”.

**Usage**

```

din(data, q.matrix, skillclasses=NULL,
    conv.crit=0.001, dev.crit=10^(-5), maxit=500,
    constraint.guess=NULL, constraint.slip=NULL,
    guess.init=rep(0.2, ncol(data)), slip.init=guess.init,
    guess.equal=FALSE, slip.equal=FALSE, zeroprob.skillclasses=NULL,
    weights=rep(1, nrow(data)), rule="DINA",
    wgt.overrelax=0, wgttest.overrelax=FALSE, param.history=FALSE,
    seed=0, progress=TRUE, guess.min=0, slip.min=0, guess.max=1, slip.max=1)

## S3 method for class 'din'
print(x, ...)

```

**Arguments**

data	A required $N \times J$ data matrix containing the binary responses, 0 or 1, of $N$ respondents to $J$ test items, where 1 denotes a correct response and 0 an incorrect one. The $n$ th row of the matrix represents the binary response pattern of respondent $n$ . NA values are allowed.
q.matrix	A required binary $J \times K$ containing the attributes not required or required, 0 or 1, to master the items. The $j$ th row of the matrix is a binary indicator vector indicating which attributes are not required (coded by 0) and which attributes are required (coded by 1) to master item $j$ .
skillclasses	An optional matrix for determining the skill space. The argument can be used if a user wants less than $2^K$ skill classes.
conv.crit	A numeric which defines the termination criterion of iterations in the parameter estimation process. Iteration ends if the maximal change in parameter estimates is below this value.
dev.crit	A numeric value which defines the termination criterion of iterations in relative change in deviance.
maxit	An integer which defines the maximum number of iterations in the estimation process.
constraint.guess	An optional matrix of fixed guessing parameters. The first column of this matrix indicates the numbers of the items whose guessing parameters are fixed and the second column the values the guessing parameters are fixed to.

<code>constraint.slip</code>	An optional matrix of fixed slipping parameters. The first column of this matrix indicates the numbers of the items whose slipping parameters are fixed and the second column the values the slipping parameters are fixed to.
<code>guess.init</code>	An optional initial vector of guessing parameters. Guessing parameters are bounded between 0 and 1.
<code>slip.init</code>	An optional initial vector of slipping parameters. Slipping parameters are bounded between 0 and 1.
<code>guess.equal</code>	An optional logical indicating if all guessing parameters are equal to each other. Default is FALSE.
<code>slip.equal</code>	An optional logical indicating if all slipping parameters are equal to each other. Default is FALSE.
<code>zeroprob.skillclasses</code>	An optional vector of integers which indicates which skill classes should have zero probability. Default is NULL (no skill classes with zero probability).
<code>weights</code>	An optional vector of weights for the response pattern. Non-integer weights allow for different sampling schemes.
<code>rule</code>	An optional character string or vector of character strings specifying the model rule that is used. The character strings must be of "DINA" or "DINO". If a vector of character strings is specified, implying an item wise condensation rule, the vector must be of length $J$ , which is the number of items. The default is the condensation rule "DINA" for all items.
<code>wgt.overrelax</code>	A parameter which is relevant when an overrelaxation algorithm is used
<code>wgtest.overrelax</code>	A logical which indicates if the overrelaxation parameter being estimated during iterations
<code>param.history</code>	A logical which indicates if the parameter history during iterations should be saved. The default is FALSE.
<code>seed</code>	Simulation seed for initial parameters. A value of zero corresponds to deterministic starting values, an integer value different from zero to random initial values with <code>set.seed(seed)</code> .
<code>progress</code>	An optional logical indicating whether the function should print the progress of iteration in the estimation process.
<code>guess.min</code>	Minimum value of guessing parameters to be estimated.
<code>slip.min</code>	Minimum value of slipping parameters to be estimated.
<code>guess.max</code>	Maximum value of guessing parameters to be estimated.
<code>slip.max</code>	Maximum value of slipping parameters to be estimated.
<code>x</code>	Object of class <code>din</code>
<code>...</code>	Further arguments to be passed

### Details

In the CDM DINA (deterministic-input, noisy-and-gate; de la Torre & Douglas, 2004) and DINO (deterministic-input, noisy-or-gate; Templin & Henson, 2006) models endorsement probabilities



are modeled based on guessing and slipping parameters, given the different skill classes. The probability of respondent  $n$  (or corresponding respondents class  $n$ ) for solving item  $j$  is calculated as a function of the respondent's latent response  $\eta_{nj}$  and the guessing and slipping rates  $g_j$  and  $s_j$  for item  $j$  conditional on the respondent's skill class  $\alpha_n$ :

$$P(X_{nj} = 1|\alpha_n) = g_j^{(1-\eta_{nj})}(1 - s_j)^{\eta_{nj}}.$$

The respondent's latent response (class)  $\eta_{nj}$  is a binary number, 0 or 1, where 1 indicates presence of all (rule="DINO") or at least one (rule="DINA") required skill(s) for item  $j$ , respectively.

DINA and DINO parameter estimation is performed by maximization of the marginal likelihood of the data. The a priori distribution of the skill vectors is a uniform distribution. The implementation follows the EM algorithm by de la Torre (2009).

The function `din` returns an object of the class `din` (see 'Value'), for which `plot`, `print`, and `summary` methods are provided; `plot.din`, `print.din`, and `summary.din`, respectively.

### Value

<code>coef</code>	Estimated model parameters. Note that only freely estimated parameters are included.
<code>item</code>	A data frame giving for each item condensation rule, the estimated guessing and slipping parameters and their standard errors. All entries are rounded to 3 digits.
<code>guess</code>	A data frame giving the estimated guessing parameters and their standard errors for each item.
<code>slip</code>	A data frame giving the estimated slipping parameters and their standard errors for each item.
<code>IDI</code>	A matrix giving the item discrimination index (IDI; Lee, de la Torre & Park, 2012) for each item $j$ $IDI_j = 1 - s_j - g_j,$ <p>where a high IDI corresponds to good test items which have both low guessing and slipping rates. Note that a negative IDI indicates violation of the monotonicity condition <math>g_j &lt; 1 - s_j</math>. See <code>din</code> for help.</p>
<code>itemfit.rmsea</code>	The RMSEA item fit index (see <code>itemfit.rmsea</code> ).
<code>mean.rmsea</code>	Mean of RMSEA item fit indexes.
<code>loglike</code>	A numeric giving the value of the maximized log likelihood.
<code>AIC</code>	A numeric giving the AIC value of the model.
<code>BIC</code>	A numeric giving the BIC value of the model.
<code>Npars</code>	Number of estimated parameters
<code>posterior</code>	A matrix given the posterior skill distribution for all respondents. The $n$ th row of the matrix gives the probabilities for respondent $n$ to possess any of the $2^K$ skill classes.
<code>like</code>	A matrix giving the values of the maximized likelihood for all respondents.
<code>data</code>	The input matrix of binary response data.
<code>q.matrix</code>	The input matrix of the required attributes.

pattern	A matrix giving the skill classes leading to highest endorsement probability for the respective response pattern ( <code>mle.est</code> ) with the corresponding posterior class probability ( <code>mle.post</code> ), the attribute classes having the highest occurrence posterior probability given the response pattern ( <code>map.est</code> ) with the corresponding posterior class probability ( <code>map.post</code> ), and the estimated posterior for each response pattern ( <code>pattern</code> ).
attribute.patt	A data frame giving the estimated occurrence probabilities of the skill classes and the expected frequency of the attribute classes given the model.
skill.patt	A matrix given the population prevalences of the skills.
subj.pattern	A vector of strings indicating the item response pattern for each subject.
attribute.patt.splitted	A dataframe giving the skill class of the respondents.
display	A character giving the model specified under rule.
item.patt.split	A matrix giving the splitted response pattern.
item.patt.freq	A numeric vector given the frequencies of the response pattern in <code>item.patt.split</code> .
seed	Used simulation seed for initial parameters
partable	Parameter table which is used for <code>coef</code> and <code>vcov</code> .
vcov.derived	Design matrix for extended set of parameters in <code>vcov</code> .
converged	Logical indicating whether convergence was achieved.
control	Optimization parameters used in estimation

### Note

The calculation of standard errors using sampling weights which represent multistage sampling schemes is not correct. Please use replication methods (like Jackknife) instead.

### References

- de la Torre, J. (2009). DINA model parameter estimation: A didactic. *Journal of Educational and Behavioral Statistics*, *34*, 115–130.
- de la Torre, J., & Douglas, J. (2004). Higher-order latent trait models for cognitive diagnosis. *Psychometrika*, *69*, 333–353.
- Lee, Y.-S., de la Torre, J., & Park, Y. S. (2012). Relationships between cognitive diagnosis, CTT, and IRT indices: An empirical investigation. *Asia Pacific Educational Research*, *13*, 333–345.
- Rupp, A. A., Templin, J., & Henson, R. A. (2010). *Diagnostic Measurement: Theory, Methods, and Applications*. New York: The Guilford Press.
- Templin, J., & Henson, R. (2006). Measurement of psychological disorders using cognitive diagnosis models. *Psychological Methods*, *11*, 287–305.

**See Also**

`plot.din`, the S3 method for plotting objects of the class `din`; `print.din`, the S3 method for printing objects of the class `din`; `summary.din`, the S3 method for summarizing objects of the class `din`, which creates objects of the class `summary.din`; `din`, the main function for DINA and DINO parameter estimation, which creates objects of the class `din`.

See the `gdina` function for the estimation of the generalized DINA (GDINA) model.

For assessment of model fit see `modelfit.cor.din` and `anova.din`.

See `itemfit.sx2` for item fit statistics.

See `discrim.index` for computing discrimination indices.

See also `CDM-package` for general information about this package.

See the `NPCD::JMLE` function in the **NPCD** package for joint maximum likelihood estimation of the DINA, DINO and NIDA model.

See the `dina::DINA_Gibbs` function in the **dina** package for MCMC based estimation of the DINA model.

**Examples**

```
#####
# EXAMPLE 1: Examples based on dataset fractions.subtraction.data
#####

## dataset fractions.subtraction.data and corresponding Q-Matrix
head(fraction.subtraction.data)
fraction.subtraction.qmatrix

## Misspecification in parameter specification for method CDM::din()
## leads to warnings and terminates estimation procedure. E.g.,

# See Q-Matrix specification
fractions.dina.warning1 <- CDM::din(data=fraction.subtraction.data,
  q.matrix=t(fraction.subtraction.qmatrix))

# See guess.init specification
fractions.dina.warning2 <- CDM::din(data=fraction.subtraction.data,
  q.matrix=fraction.subtraction.qmatrix, guess.init=rep(1.2,
  ncol(fraction.subtraction.data)))

# See rule specification
fractions.dina.warning3 <- CDM::din(data=fraction.subtraction.data,
  q.matrix=fraction.subtraction.qmatrix, rule=c(rep("DINA",
  10), rep("DINO", 9)))

## Parameter estimation of DINA model
# rule="DINA" is default
fractions.dina <- CDM::din(data=fraction.subtraction.data,
  q.matrix=fraction.subtraction.qmatrix, rule="DINA")
attributes(fractions.dina)
str(fractions.dina)
```

```

## For instance assessing the guessing parameters through
## assignment
fractions.dina$guess

## corresponding summaries, including IDI,
## most frequent skill classes and information
## criteria AIC and BIC
summary(fractions.dina)

## In particular, assessing detailed summary through assignment
detailed.summary.fs <- summary(fractions.dina)
str(detailed.summary.fs)

## Item discrimination index of item 8 is too low. This is also
## visualized in the first plot
plot(fractions.dina)

## The reason therefore is a high guessing parameter
round(fractions.dina$guess[,1], 2)

## Estimate DINA model with different random initial parameters using seed=1345
fractions.dina1 <- CDM::din(data=fraction.subtraction.data,
  q.matrix=fraction.subtraction.qmatrix, rule="DINA", seed=1345)

## Fix the guessing parameters of items 5, 8 and 9 equal to .20
# define a constraint.guess matrix
constraint.guess <- matrix(c(5,8,9, rep(0.2, 3)), ncol=2)
fractions.dina.fixed <- CDM::din(data=fraction.subtraction.data,
  q.matrix=fraction.subtraction.qmatrix,
  constraint.guess=constraint.guess)

## The second plot shows the expected (MAP) and observed skill
## probabilities. The third plot visualizes the skill class
## occurrence probabilities; Only the 'top.n.skill.classes' most frequent
## skill classes are labeled; it is obvious that the skill class '11111111'
## (all skills are mastered) is the most probable in this population.
## The fourth plot shows the skill probabilities conditional on response
## patterns; in this population the skills 3 and 6 seem to be
## mastered easier than the others. The fourth plot shows the
## skill probabilities conditional on a specified response
## pattern; it is shown whether a skill is mastered (above
## .5+'uncertainty') unclassifiable (within the boundaries) or
## not mastered (below .5-'uncertainty'). In this case, the
## 527th respondent was chosen; if no response pattern is
## specified, the plot will not be shown (of course)
pattern <- paste(fraction.subtraction.data[527, ], collapse="")
plot(fractions.dina, pattern=pattern, display.nr=4)

#uncertainty=0.1, top.n.skill.classes=6 are default
plot(fractions.dina.fixed, uncertainty=0.1, top.n.skill.classes=6,
  pattern=pattern)

## Not run:

```

```
#####
# EXAMPLE 2: Examples based on dataset sim.dina
#####

# DINA Model
d1 <- CDM::din(sim.dina, q.matr=sim.qmatrix, rule="DINA",
  conv.crit=0.01, maxit=500, progress=TRUE)
summary(d1)

# DINA model with hierarchical skill classes (Hierarchical DINA model)
# 1st step: estimate an initial full model to look at the indexing
#   of skill classes
d0 <- CDM::din(sim.dina, q.matr=sim.qmatrix, maxit=1)
d0$attribute.patt.splitted
#   [,1] [,2] [,3]
# [1,]  0  0  0
# [2,]  1  0  0
# [3,]  0  1  0
# [4,]  0  0  1
# [5,]  1  1  0
# [6,]  1  0  1
# [7,]  0  1  1
# [8,]  1  1  1
#
# In this example, following hierarchical skill classes are only allowed:
# 000, 001, 011, 111
# We define therefore a vector of indices for skill classes with
# zero probabilities (see entries in the rows of the matrix
# d0$attribute.patt.splitted above)
zeroprob.skillclasses <- c(2,3,5,6) # classes 100, 010, 110, 101
# estimate the hierarchical DINA model
d1a <- CDM::din(sim.dina, q.matr=sim.qmatrix,
  zeroprob.skillclasses=zeroprob.skillclasses )
summary(d1a)

# Mixed DINA and DINO Model
d1b <- CDM::din(sim.dina, q.matr=sim.qmatrix, rule=
  c(rep("DINA", 7), rep("DINO", 2)), conv.crit=0.01,
  maxit=500, progress=FALSE)
summary(d1b)

# DINO Model
d2 <- CDM::din(sim.dina, q.matr=sim.qmatrix, rule="DINO",
  conv.crit=0.01, maxit=500, progress=FALSE)
summary(d2)

# Comparison of DINA and DINO estimates
lapply(list("guessing"=rbind("DINA"=d1$guess[,1],
  "DINO"=d2$guess[,1]), "slipping"=rbind("DINA"=
  d1$slip[,1], "DINO"=d2$slip[,1])), round, 2)

# Comparison of the information criteria
c("DINA"=d1$AIC, "MIXED"=d1b$AIC, "DINO"=d2$AIC)
```

```

# following estimates:
d1$coef          # guessing and slipping parameter
d1$guess         # guessing parameter
d1$slip          # slipping parameter
d1$skill.patt    # probabilities for skills
d1$attribute.patt # skill classes with probabilities
d1$subj.pattern  # pattern per subject

# posterior probabilities for every response pattern
d1$posterior

# Equal guessing parameters
d2a <- CDM::din( data=sim.dina, q.matrix=sim.qmatrix,
                guess.equal=TRUE, slip.equal=FALSE )
d2a$coef

# Equal guessing and slipping parameters
d2b <- CDM::din( data=sim.dina, q.matrix=sim.qmatrix,
                guess.equal=TRUE, slip.equal=TRUE )
d2b$coef

#####
# EXAMPLE 3: Examples based on dataset sim.dino
#####

# DINO Estimation
d3 <- CDM::din(sim.dino, q.matr=sim.qmatrix, rule="DINO",
              conv.crit=0.005, progress=FALSE)

# Mixed DINA and DINO Model
d3b <- CDM::din(sim.dino, q.matr=sim.qmatrix,
               rule=c(rep("DINA", 4), rep("DINO", 5)), conv.crit=0.001,
               progress=FALSE)

# DINA Estimation
d4 <- CDM::din(sim.dino, q.matr=sim.qmatrix, rule="DINA",
              conv.crit=0.005, progress=FALSE)

# Comparison of DINA and DINO estimates
lapply(list("guessing"=rbind("DINO"=d3$guess[,1], "DINA"=d4$guess[,1]),
           "slipping"=rbind("DINO"=d3$slip[,1], "DINA"=d4$slip[,1])), round, 2)

# Comparison of the information criteria
c("DINO"=d3$AIC, "MIXED"=d3b$AIC, "DINA"=d4$AIC)

#####
# EXAMPLE 4: Example estimation with weights based on dataset sim.dina
#####

# Here, a weighted maximum likelihood estimation is used
# This could be useful for survey data.

```

```

# i.e. first 200 persons have weight 2, the other have weight 1
(weights <- c(rep(2, 200), rep(1, 200)))

d5 <- CDM::din(sim.dina, sim.qmatrix, rule="DINA", conv.crit=
  0.005, weights=weights, progress=FALSE)

# Comparison of the information criteria
c("DINA"=d1$AIC, "WEIGHTS"=d5$AIC)

#####
# EXAMPLE 5: Example estimation within a balanced incomplete
##           block (BIB) design generated on dataset sim.dina
#####

# generate BIB data

# The next example shows that the din function works for
# (relatively arbitrary) missing value pattern

# Here, a missing by design is generated in the dataset dinadat.bib
sim.dina.bib <- sim.dina
sim.dina.bib[1:100, 1:3] <- NA
sim.dina.bib[101:300, 4:8] <- NA
sim.dina.bib[301:400, c(1,2,9)] <- NA

d6 <- CDM::din(sim.dina.bib, sim.qmatrix, rule="DINA",
  conv.crit=0.0005, weights=weights, maxit=200)

d7 <- CDM::din(sim.dina.bib, sim.qmatrix, rule="DINO",
  conv.crit=0.005, weights=weights)

# Comparison of DINA and DINO estimates
lapply(list("guessing"=rbind("DINA"=d6$guess[,1],
  "DINO"=d7$guess[,1]), "slipping"=rbind("DINA"=
  d6$slip[,1], "DINO"=d7$slip[,1])), round, 2)

#####
# EXAMPLE 6: DINA model with attribute hierarchy
#####

set.seed(987)
# assumed skill distribution: P(000)=P(100)=P(110)=P(111)=.245 and
# "deviant pattern": P(010)=.02
K <- 3 # number of skills

# define alpha
alpha <- scan()
  0 0 0
  1 0 0
  1 1 0
  1 1 1
  0 1 0

```

```

alpha <- matrix( alpha, length(alpha)/K, K, byrow=TRUE )
alpha <- alpha[ c( rep(1:4,each=245), rep(5,20) ), ]

# define Q-matrix
q.matrix <- scan()
  1 0 0  1 0 0  1 0 0
  0 1 0  0 1 0  0 1 0
  0 0 1  0 1 0  0 0 1
  1 1 0  1 0 1  0 1 1

q.matrix <- matrix( q.matrix, nrow=length(q.matrix)/K, ncol=K, byrow=TRUE )

# simulate DINA data
dat <- CDM::sim.din( alpha=alpha, q.matrix=q.matrix )$dat

**** Model 1: estimate DINA model | no skill space restriction
mod1 <- CDM::din( dat, q.matrix )

**** Model 2: DINA model | hierarchy A2 > A3
B <- "A2 > A3"
skill.names <- paste0("A",1:3)
skill.space <- CDM::skill.space.hierarchy( B, skill.names )$skill.space.reduced
mod2 <- CDM::din( dat, q.matrix, skill.classes=skill.space )

**** Model 3: DINA model | linear hierarchy A1 > A2 > A3
# This is a misspecified model because due to P(010)=.02 the relation A1>A2
# does not hold.
B <- "A1 > A2
      A2 > A3"
skill.names <- paste0("A",1:3)
skill.space <- CDM::skill.space.hierarchy( B, skill.names )$skill.space.reduced
mod3 <- CDM::din( dat, q.matrix, skill.classes=skill.space )

**** Model 4: 2PL model in gdm
mod4 <- CDM::gdm( dat, theta.k=seq(-5,5,len=21),
                 decrease.increments=TRUE, skill.space="normal" )
summary(mod4)

anova(mod1,mod2)
##      Model  loglike Deviance Npars      AIC      BIC Chisq df      p
##  2 Model 2 -7052.460 14104.92   29 14162.92 14305.24 0.9174 2 0.63211
##  1 Model 1 -7052.001 14104.00   31 14166.00 14318.14    NA NA    NA

anova(mod2,mod3)
##      Model  loglike Deviance Npars      AIC      BIC Chisq df      p
##  2 Model 2 -7059.058 14118.12   27 14172.12 14304.63 13.19618 2 0.00136
##  1 Model 1 -7052.460 14104.92   29 14162.92 14305.24    NA NA    NA

anova(mod2,mod4)
##      Model  loglike Deviance Npars      AIC      BIC Chisq df      p
##  2 Model 2 -7220.05 14440.10   24 14488.10 14605.89 335.1805 5 0
##  1 Model 1 -7052.46 14104.92   29 14162.92 14305.24    NA NA NA

```



```

# compare fit statistics
summary( CDM::modelfit.cor.din( mod2 ) )
summary( CDM::modelfit.cor.din( mod4 ) )

#####
# EXAMPLE 7: Fitting the basic local independence model (BLIM) with din
#####

library(pks)
data(DoignonFalmagne7, package="pks")
## str(DoignonFalmagne7)
## $ K : int [1:9, 1:5] 0 1 0 1 1 1 1 1 1 0 ...
## ..- attr(*, "dimnames")=List of 2
## .. .$ : chr [1:9] "00000" "10000" "01000" "11000" ...
## .. .$ : chr [1:5] "a" "b" "c" "d" ...
## $ N.R: Named int [1:32] 80 92 89 3 2 1 89 16 18 10 ...
## ..- attr(*, "names")=chr [1:32] "00000" "10000" "01000" "00100" ...

# The idea is to fit the local independence model with the din function.
# This can be accomplished by specifying a DINO model with
# prespecified skill classes.

# extract dataset
dat <- as.numeric( unlist( sapply( names(DoignonFalmagne7$N.R),
  FUN=function( ll){ strsplit( ll, split="") } ) ) )
dat <- matrix( dat, ncol=5, byrow=TRUE )
colnames(dat) <- colnames(DoignonFalmagne7$K)
rownames(dat) <- names(DoignonFalmagne7$N.R)

# sample weights
weights <- DoignonFalmagne7$N.R

# define Q-matrix
q.matrix <- t(DoignonFalmagne7$K)
v1 <- colnames(q.matrix) <- paste0("S", colnames(q.matrix))
q.matrix <- q.matrix[, - 1] # remove S00000

# define skill classes
SC <- ncol(q.matrix)
skillclasses <- matrix( 0, nrow=SC+1, ncol=SC)
colnames(skillclasses) <- colnames(q.matrix)
rownames(skillclasses) <- v1
skillclasses[ cbind( 2:(SC+1), 1:SC ) ] <- 1

# estimate BLIM with din function
mod1 <- CDM::din(data=dat, q.matrix=q.matrix, skillclasses=skillclasses,
  rule="DINO", weights=weights )
summary(mod1)
## Item parameters
## item guess slip IDI rmsea
## a a 0.158 0.162 0.680 0.011
## b b 0.145 0.159 0.696 0.009
## c c 0.008 0.181 0.811 0.001

```

```

## d d 0.012 0.129 0.859 0.001
## e e 0.025 0.146 0.828 0.007

# estimate basic local independence model with pks package
mod2 <- pks::blim(K, N.R, method="ML") # maximum likelihood estimation by EM algorithm
mod2
## Error and guessing parameters
## beta eta
## a 0.164871 0.103065
## b 0.163113 0.095074
## c 0.188839 0.000004
## d 0.079835 0.000003
## e 0.088648 0.019910

## End(Not run)

```

---

din.deterministic	<i>Deterministic Classification and Joint Maximum Likelihood Estimation of the Mixed DINA/DINO Model</i>
-------------------	--

---

## Description

This function allows the estimation of the mixed DINA/DINO model by joint maximum likelihood and a deterministic classification based on ideal latent responses.

## Usage

```

din.deterministic(dat, q.matrix, rule="DINA", method="JML", conv=0.001,
  maxiter=300, increment.factor=1.05, progress=TRUE)

```

## Arguments

dat	Data frame of dichotomous item responses
q.matrix	Q-matrix with binary entries (see <a href="#">din</a> ).
rule	The condensation rule (see <a href="#">din</a> ).
method	Estimation method. The default is joint maximum likelihood estimation (JML). Other options include an adaptive estimation of guessing and slipping parameters (adaptive) while using these estimated parameters as weights in the individual deviation function and classification based on the Hamming distance (hamming) and the weighted Hamming distance (weighted.hamming) (see Chiu & Douglas, 2013).
conv	Convergence criterion for guessing and slipping parameters
maxiter	Maximum number of iterations
increment.factor	A numeric value of at least one which could help to improve convergence behavior and decreases parameter increments in every iteration. This option is disabled by setting this argument to 1.
progress	An optional logical indicating whether the function should print the progress of iteration in the estimation process.

**Value**

A list with following entries

attr.est	Estimated attribute patterns
criterion	Criterion of the classification function. For joint maximum likelihood it is the deviance.
guess	Estimated guessing parameters
slip	Estimated slipping parameters
prederror	Average individual prediction error
q.matrix	Used Q-matrix
dat	Used data frame

**References**

Chiu, C. Y., & Douglas, J. (2013). A nonparametric approach to cognitive diagnosis by proximity to ideal response patterns. *Journal of Classification*, 30, 225-250.

**See Also**

For estimating the mixed DINA/DINO model using marginal maximum likelihood estimation see [din](#).

See also the NPCD : JMLE function in the **NPCD** package for joint maximum likelihood estimation of the DINA or the DINO model.

**Examples**

```
#####
# EXAMPLE 1: 13 items and 3 attributes
#####

set.seed(679)
N <- 3000
# specify true Q-matrix
q.matrix <- matrix( 0, 13, 3 )
q.matrix[1:3,1] <- 1
q.matrix[4:6,2] <- 1
q.matrix[7:9,3] <- 1
q.matrix[10,] <- c(1,1,0)
q.matrix[11,] <- c(1,0,1)
q.matrix[12,] <- c(0,1,1)
q.matrix[13,] <- c(1,1,1)
q.matrix <- rbind( q.matrix, q.matrix )
colnames(q.matrix) <- paste0("Attr",1:ncol(q.matrix))

# simulate data according to the DINA model
dat <- CDM::sim.din( N=N, q.matrix)$dat

# Joint maximum likelihood estimation (the default: method="JML")
res1 <- CDM::din.deterministic( dat, q.matrix )
```

```

# Adaptive estimation of guessing and slipping parameters
res <- CDM::din.deterministic( dat, q.matrix, method="adaptive" )

# Classification using Hamming distance
res <- CDM::din.deterministic( dat, q.matrix, method="hamming" )

# Classification using weighted Hamming distance
res <- CDM::din.deterministic( dat, q.matrix, method="weighted.hamming" )

## Not run:
##### load NPCD library for JML estimation
library(NPCD)

# DINA model
res <- NPCD::JMLE( Y=dat[1:100,], Q=q.matrix, model="DINA" )
as.data.frame(res$par.est ) # item parameters
res$alpha.est             # skill classifications

# RRUM model
res <- NPCD::JMLE( Y=dat[1:100,], Q=q.matrix, model="RRUM" )
as.data.frame(res$par.est )

## End(Not run)

```

---

din.equivalent.class    *Calculation of Equivalent Skill Classes in the DINA/DINO Model*

---

## Description

This function computes indistinguishable skill classes for the DINA and DINO model (Gross & George, 2014; Zhang, DeCarlo & Ying, 2013).

## Usage

```
din.equivalent.class(q.matrix, rule="DINA")
```

## Arguments

q.matrix	The Q-matrix (see <a href="#">din</a> ).
rule	The condensation rule. If it is a string, then the rule applies to all items. If it is a vector, then for each item DINA or DINO rule can be chosen.

## Value

A list with following entries:

latent.responseM	Matrix of latent responses
------------------	----------------------------

latent.response	Latent responses represented as a string
S	Matrix containing all skill classes
gini	Gini coefficient of the frequency distribution of identifiable skill classes which result in the same latent response
skillclasses	Data frame with skill class (skillclass), latent responses (latent.response) and an identifier for distinguishable skill classes (distinguish.class).

## References

Gross, J. & George, A. C. (2014). On prerequisite relations between attributes in noncompensatory diagnostic classification. *Methodology*, *10*(3), 100-107.

Zhang, S. S., DeCarlo, L. T., & Ying, Z. (2013). Non-identifiability, equivalence classes, and attribute-specific classification in Q-matrix based cognitive diagnosis models. *arXiv preprint, arXiv:1303.0426*.

## Examples

```
#####
# EXAMPLE 1: Equivalency classes for DINA model for fraction subtraction data
#####

#-- DINA models

data(data.fraction2, package="CDM")

# first Q-matrix
Q1 <- data.fraction2$q.matrix1
m1 <- CDM::din.equivalent.class( q.matrix=Q1, rule="DINA" )
## 8 Skill classes | 5 distinguishable skill classes | Gini coefficient=0.3

# second Q-matrix
Q1 <- data.fraction2$q.matrix2
m1 <- CDM::din.equivalent.class( q.matrix=Q1, rule="DINA" )
## 32 Skill classes | 9 distinguishable skill classes | Gini coefficient=0.5

# third Q-matrix
Q1 <- data.fraction2$q.matrix3
m1 <- CDM::din.equivalent.class( q.matrix=Q1, rule="DINA" )
## 8 Skill classes | 8 distinguishable skill classes | Gini coefficient=0

# original fraction subtraction data
m1 <- CDM::din.equivalent.class( q.matrix=CDM::fraction.subtraction.qmatrix, rule="DINA")
## 256 Skill classes | 58 distinguishable skill classes | Gini coefficient=0.659
```

**Description**

Q-matrix entries can be modified by the Q-matrix validation method of de la Torre (2008). After estimating a mixed DINA/DINO model using the `din` function, item parameters and the item discrimination parameters  $IDI_j$  are recalculated. Q-matrix rows are determined by maximizing the estimated item discrimination index  $IDI_j = 1 - s_j - g_j$ .

**Usage**

```
din.validate.qmatrix(object, IDI_diff=.02, print=TRUE)
```

**Arguments**

<code>object</code>	Object of class <code>din</code>
<code>IDI_diff</code>	Minimum difference in IDI values for choosing a new Q-matrix vector
<code>print</code>	An optional logical indicating whether the function should print the progress of iteration in the estimation process.

**Value**

A list with following entries:

<code>coef.modified</code>	Estimated parameters by applying Q-matrix modifications
<code>coef.modified.short</code>	A shortened matrix of <code>coef.modified</code> . Only Q-matrix rows which increase the $IDI$ are displayed.
<code>q.matrix.prop</code>	The proposed Q-matrix by Q-matrix validation.

**References**

Chiu, C. Y. (2013). Statistical refinement of the Q-matrix in cognitive diagnosis. *Applied Psychological Measurement*, 37, 598-618.

de la Torre, J. (2008). An empirically based method of Q-matrix validation for the DINA model: Development and applications. *Journal of Educational Measurement*, 45, 343-362.

**See Also**

The mixed DINA/DINO model can be estimated with `din`.

See Chiu (2013) for an alternative estimation approach based on residual sum of squares which is implemented `NPCD::Qrefine` function in the **NPCD** package.

See the `GDINA::Qval` function in the **GDINA** package for extended functionality.

**Examples**

```
#####
# EXAMPLE 1: Detection of a mis-specified Q-matrix
#####

set.seed(679)
```

```

# specify true Q-matrix
q.matrix <- matrix( 0, 12, 3 )
q.matrix[1:3,1] <- 1
q.matrix[4:6,2] <- 1
q.matrix[7:9,3] <- 1
q.matrix[10,] <- c(1,1,0)
q.matrix[11,] <- c(1,0,1)
q.matrix[12,] <- c(0,1,1)
# simulate data
dat <- CDM::sim.din( N=4000, q.matrix)$dat
# incorrectly modify Q-matrix rows 1 and 10
Q1 <- q.matrix
Q1[1,] <- c(1,1,0)
Q1[10,] <- c(1,0,0)
# estimate DINA model
mod <- CDM::din( dat, q.matr=Q1, rule="DINA")
# apply Q-matrix validation
res <- CDM::din.validate.qmatrix( mod )
## item itemindex Skill1 Skill2 Skill3 guess slip IDI qmatrix.orig IDI.orig delta.IDI max.IDI
## I001      1      1      0      0 0.309 0.251 0.440          0  0.431  0.009 0.440
## I010     10      1      1      0 0.235 0.329 0.437          0  0.320  0.117 0.437
## I010     10      1      1      1 0.296 0.301 0.403          0  0.320  0.083 0.437
##
## Proposed Q-matrix:
##
##           Skill1 Skill2 Skill3
## Item1         1      0      0
## Item2         1      0      0
## Item3         1      0      0
## Item4         0      1      0
## Item5         0      1      0
## Item6         0      1      0
## Item7         0      0      1
## Item8         0      0      1
## Item9         0      0      1
## Item10        1      1      0
## Item11        1      0      1
## Item12        0      1      1

## Not run:
#####
# Q-matrix estimation ('Qrefine') in the NPCD package
# See Chiu (2013, APM).
#####

library(NPCD)
Qrefine.out <- NPCD::Qrefine( dat, Q1, gate="AND", max.ite=50)
print(Qrefine.out)
## The modified Q-matrix
##           Attribute 1 Attribute 2 Attribute 3
## Item 1             1             0             0
## Item 2             1             0             0
## Item 3             1             0             0

```

```

## Item 4      0      1      0
## Item 5      0      1      0
## Item 6      0      1      0
## Item 7      0      0      1
## Item 8      0      0      1
## Item 9      0      0      1
## Item 10     1      1      0
## Item 11     1      0      1
## Item 12     0      1      1
##
## The modified entries
##      Item Attribute
## [1,]  1           2
## [2,] 10           2

plot(Qrefine.out)

## End(Not run)

```

---

din\_identifiability    *Identifiability Conditions of the DINA Model*

---

### Description

Check necessary and sufficient identifiability conditions of the DINA model according Gu and Xu (xxxx) for a given Q-matrix.

### Usage

```

din_identifiability(q.matrix)

## S3 method for class 'din_identifiability'
summary(object, ...)

```

### Arguments

q.matrix	Q-matrix
object	Object of class din_identifiability
...	Further arguments to be passed

### Value

List with values

dina_identified	Logical indicating whether the DINA model is identified
index_single	Condition 1: vector of logicals indicating whether skills are measured by at least one item with a single loading



is\_three\_items Condition 2: vector of logicals indicating whether skills are measured by at least three items

submat\_distinct Condition 3: logical indicating whether all columns of the submatrix  $Q^*$  are distinct.

## References

Gu, Y., & Xu, G. (2018). The sufficient and necessary condition for the identifiability and estimability of the DINA model. *Psychometrika*, *xx(xx)*, xxx-xxx. <https://doi.org/10.1007/s11336-018-9619-8>

## See Also

See [din.equivalent.class](#) for equivalent (i.e., non-distinguishable) skill classes in the DINA model.

## Examples

```
#####
# EXAMPLE 1: Some examples of Gu and Xu (2019)
#####

#* Matrix 1 in Equation (5) of Gu & Xu (2019)
Q1 <- diag(3)
Q2 <- matrix( scan(text="1 1 0 1 0 1 1 1 1 1 1"), ncol=3, byrow=TRUE)
Q <- rbind(Q1, Q2)

res <- CDM::din_identifiability(q.matrix=Q)
summary(res)

# remove two items
res <- CDM::din_identifiability(q.matrix=Q[-c(2,5),])
summary(res)

#* Matrix 1 in Equation (6) of Gu & Xu (2019)
Q1 <- diag(3)
Q2 <- matrix( c(1,1,1), nrow=4, ncol=3, byrow=TRUE)
Q <- rbind(Q1, Q2)

res <- CDM::din_identifiability(q.matrix=Q)
summary(res)
```

---

discrim.index

*Discrimination Indices at Item-Attribute, Item and Test Level*

---

## Description

Computes discrimination indices at the probability metric (de la Torre, 2008; Henson, DiBello & Stout, 2018).

**Usage**

```

discrim.index(object, ...)

## S3 method for class 'din'
discrim.index(object, ...)

## S3 method for class 'gdina'
discrim.index(object, ...)

## S3 method for class 'mcdina'
discrim.index(object, ...)

## S3 method for class 'discrim.index'
summary(object, file=NULL, digits=3, ...)

```

**Arguments**

object	Object of class <code>din</code> or <code>gdina</code> .
file	Optional file name for a file in which the summary output should be sunk
digits	Number of digits for rounding
...	Further arguments to be passed

**Details**

If item  $j$  possesses  $H_j$  categories, the item-attribute specific discrimination for attribute  $k$  according to Henson et al. (2018) is defined as

$$DI_{jk} = \frac{1}{2} \max_{\alpha} \left( \sum_{h=1}^{H_j} |P(X_j = h|\alpha) - P(X_j = h|\alpha^{(-k)})| \right)$$

where  $\alpha^{(-k)}$  and  $\alpha$  differ only in attribute  $k$ . The index  $DI_{jk}$  can be found as the value `discrim_item_attribute`. The test-level discrimination index is defined as

$$\overline{DI} = \frac{1}{J} \sum_{j=1}^J \max_k DI_{jk}$$

and can be found in `discrim_test`.

According to de la Torre (2008) and de la Torre, Rossi and van der Ark (2018), the item discrimination index (IDI) is defined as

$$IDI_j = \max_{\alpha_1, \alpha_2, h} |P(X_j = h|\alpha_1) - P(X_j = h|\alpha_2)|$$

and can be found as `idi` in the values list.

**Value**

A list with following entries

discrim_item_attribute	Discrimination indices $DI_{jk}$ at item level for each attribute
idi	Item discrimination index $IDI_j$
discrim_test	Discrimination index at test level

**References**

- de la Torre, J. (2008). An empirically based method of Q-matrix validation for the DINA model: Development and applications. *Journal of Educational Measurement*, 45, 343-362.  
<http://dx.doi.org/10.1111/j.1745-3984.2008.00069.x>
- de la Torre, J., van der Ark, L. A., & Rossi, G. (2018). Analysis of clinical data from a cognitive diagnosis modeling framework. *Measurement and Evaluation in Counseling and Development*, 51(4), 281-296. <https://doi.org/10.1080/07481756.2017.1327286>
- Henson, R., DiBello, L., & Stout, B. (2018). A generalized approach to defining item discrimination for DCMs. *Measurement: Interdisciplinary Research and Perspectives*, 16(1), 18-29.  
<http://dx.doi.org/10.1080/15366367.2018.1436855>

**See Also**

See [cdi.kli](#) for discrimination indices based on the Kullback-Leibler information.

For a fitted model `mod` in the **GDINA** package, discrimination indices can be extracted by the method `extract(mod, "discrim")` ([GDINA::extract](#)).

**Examples**

```
## Not run:
#####
# EXAMPLE 1: DINA and GDINA model
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

#-- fit GDINA and DINA model
mod1 <- CDM::gdina( sim.dina, q.matrix=sim.qmatrix )
mod2 <- CDM::din( sim.dina, q.matrix=sim.qmatrix )

#-- compute discrimination indices
dimod1 <- CDM::discrim.index(mod1)
dimod2 <- CDM::discrim.index(mod2)
summary(dimod1)
summary(dimod2)

## End(Not run)
```

entropy.lca

*Test-specific and Item-specific Entropy for Latent Class Models***Description**

Computes test-specific and item-specific entropy as test-diagnostic criteria of cognitive diagnostic models (Asparouhov & Muthen, 2014).

**Usage**

```
entropy.lca(object)

## S3 method for class 'entropy.lca'
summary(object, digits=2, ...)
```

**Arguments**

object	Object of class <code>din</code> , <code>gdina</code> or <code>mcdina</code> . For the summary method, it is the result of <code>entropy.lca</code> .
digits	Number of digits to round
...	Further arguments to be passed

**Value**

A list with the data frame entropy as an entry.

**References**

Asparouhov, T. & Muthen, B. (2014). *Variable-specific entropy contribution*. Technical Appendix. [http://www.statmodel.com/7\\_3\\_papers.shtml](http://www.statmodel.com/7_3_papers.shtml)

**See Also**

See `cdi.kli` for test diagnostic indices based on the Kullback-Leibler information and `cdm.est.class.accuracy` for calculating the classification accuracy.

**Examples**

```
#####
# EXAMPLE 1: Entropy for DINA model
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

# fit DINA Model
mod1 <- CDM::din( sim.dina, q.matrix=sim.qmatrix, rule="DINA")
summary(mod1)
```

```

# compute entropy for test and items
emod1 <- CDM::entropy.lca( mod1 )
summary(emod1)

## Not run:
#####
# EXAMPLE 2: Entropy for polytomous GDINA model
#####

data(data.pgdina, package="CDM")

dat <- data.pgdina$dat
q.matrix <- data.pgdina$q.matrix

# pGDINA model with "DINA rule"
mod1 <- CDM::gdina( dat, q.matrix=q.matrix, rule="DINA")
summary(mod1)

# compute entropy
emod1 <- CDM::entropy.lca( mod1 )
summary(emod1)

#####
# EXAMPLE 3: Entropy for MCDINA model
#####

data(data.cdm02, package="CDM")

dat <- data.cdm02$data
q.matrix <- data.cdm02$q.matrix

# estimate model with polytomous attribute
mod1 <- CDM::mcdina( dat, q.matrix=q.matrix )
summary(mod1)
# compute entropy
emod1 <- CDM::entropy.lca( mod1 )
summary(emod1)

## End(Not run)

```

---

## Description

This function determines a statistically equivalent DINA model given a Q-matrix using the method of von Davier (2014). Thereby, the dimension of the skill space is expanded, but in the reparameterized version, the Q-matrix has a simple structure or the IRT model is no longer be conjunctive (like in DINA) due to a redefinition of the skill space.

**Usage**

```
equivalent.dina(q.matrix, reparameterization="B")
```

**Arguments**

`q.matrix`            The Q-matrix (see [din](#))  
`reparameterization`    The used reparameterization (see von Davier, 2014). A and B are possible reparameterizations.

**Value**

A list with following entries

`q.matrix`            Original Q-matrix  
`q.matrix.ast`        Reparameterized Q-matrix  
`alpha`                Original skill space  
`alpha.ast`            Reparameterized skill space

**References**

von Davier, M. (2014). The DINA model as a constrained general diagnostic model: Two variants of a model equivalency. *British Journal of Mathematical and Statistical Psychology*, 67, 49-71.

**Examples**

```
#####
# EXAMPLE 1: Toy example
#####

# define a Q-matrix
Q <- matrix( c( 1,0,0, 0,1,0,
               0,0,1, 1,0,1, 1,1,1 ), byrow=TRUE, ncol=3 )
Q <- Q[ rep(1:(nrow(Q)),each=2), ]

# equivalent DINA model (using the default reparameterization B)
res1 <- CDM::equivalent.dina( q.matrix=Q )
res1

# equivalent DINA model (reparameterization A)
res2 <- CDM::equivalent.dina( q.matrix=Q, reparameterization="A")
res2

## Not run:
#####
# EXAMPLE 2: Estimation with two equivalent DINA models
#####

# simulate data
set.seed(789)
```

```

D <- ncol(Q)
mean.alpha <- c( -.5, .5, 0 )
r1 <- .5
Sigma.alpha <- matrix( r1, D, D ) + diag(1-r1,D)
dat1 <- CDM::sim.din( N=2000, q.matrix=Q, mean=mean.alpha, Sigma=Sigma.alpha )

# estimate DINA model
mod1 <- CDM::din( dat1$dat, q.matrix=Q )

# estimate equivalent DINA model
mod2 <- CDM::din( dat1$dat, q.matrix=res1$q.matrix.ast, skillclasses=res1$alpha.ast)
# restricted skill space must be defined by using the argument 'skillclasses'

# compare model summaries
summary(mod2)
summary(mod1)

# compare estimated item parameters
cbind( mod2$coef, mod1$coef )

# compare estimated skill class probabilities
round( cbind( mod2$attribute.patt, mod1$attribute.patt ), 4 )

#####
# EXAMPLE 3: Examples from von Davier (2014)
#####

# define Q-matrix
Q <- matrix( 0, nrow=8, ncol=3 )
Q[2, ] <- c(1,0,0)
Q[3, ] <- c(0,1,0)
Q[4, ] <- c(1,1,0)
Q[5, ] <- c(0,0,1)
# Q[6, ] <- c(1,0,1)
Q[6, ] <- c(0,0,1)
Q[7, ] <- c(0,1,1)
Q[8, ] <- c(1,1,1)

#- parametrization A
res1 <- CDM::equivalent.dina(q.matrix=Q, reparameterization="A")
res1

#- parametrization B
res2 <- CDM::equivalent.dina(q.matrix=Q, reparameterization="B")
res2

## End(Not run)

```

**Description**

The function `eval_likelihood` evaluates the likelihood given item responses and item response probabilities.

The function `prep_data_long_format` stores the matrix of item responses in a long format omitted all missing responses.

**Usage**

```
eval_likelihood(data, irfprob, prior=NULL, normalization=FALSE, N=NULL)
```

```
prep_data_long_format(data)
```

**Arguments**

<code>data</code>	Dataset containing item responses in wide format or long format (generated by <code>prep_data_long_format</code> ).
<code>irfprob</code>	Array containing item responses probabilities, format see <a href="#">IRT.irfprob</a>
<code>prior</code>	Optional prior (matrix or vector)
<code>normalization</code>	Logical indicating whether posterior should be normalized
<code>N</code>	Number of persons (optional)

**Value**

Numeric matrix

**Examples**

```
## Not run:
#####
# EXAMPLE 1: Likelihood data.ecpe
#####

data(data.ecpe, package="CDM")
dat <- data.ecpe$dat[,-1]
Q <- data.ecpe$q.matrix

#*** store data matrix in long format
data_long <- CDM::prep_data_long_format(data)
str(data_long)

#** estimate GDINA model
mod <- CDM::gdina(dat, q.matrix=Q)
summary(mod)

#** extract data, item response functions and prior
data <- CDM::IRT.data(mod)
irfprob <- CDM::IRT.irfprob(mod)
prob_theta <- attr( irfprob, "prob.theta")
```



```

*** compute likelihood
lmod <- CDM::eval_likelihood(data=data, irfprob=irfprob)
max( abs( lmod - CDM::IRT.likelihood(mod) ))

*** compute posterior
pmod <- CDM::eval_likelihood(data=data, irfprob=irfprob, prior=prob.theta,
                             normalization=TRUE)
max( abs( pmod - CDM::IRT.posterior(mod) ))

## End(Not run)

```

---

fraction.subtraction.data

*Fraction Subtraction Data*

---

## Description

Tatsuoka's (1984) fraction subtraction data set is comprised of responses to  $J = 20$  fraction subtraction test items from  $N = 536$  middle school students.

## Usage

```
data(fraction.subtraction.data)
```

## Format

The `fraction.subtraction.data` data frame consists of 536 rows and 20 columns, representing the responses of the  $N = 536$  students to each of the  $J = 20$  test items. Each row in the data set corresponds to the responses of a particular student. Thereby a "1" denotes that a correct response was recorded, while "0" denotes an incorrect response. The other way round, each column corresponds to all responses to a particular item.

## Details

The items used for the fraction subtraction test originally appeared in Tatsuoka (1984) and are published in Tatsuoka (2002). They can also be found in DeCarlo (2011). All test items are based on 8 attributes (e.g. convert a whole number to a fraction, separate a whole number from a fraction or simplify before subtracting). The complete list of skills can be found in [fraction.subtraction.qmatrix](#).

## Source

The Royal Statistical Society Datasets Website, Series C, Applied Statistics, Data analytic methods for latent partially ordered classification models:

URL: [http://www.blackwellpublishing.com/rss/Volumes/Cv51p2\\_read2.htm](http://www.blackwellpublishing.com/rss/Volumes/Cv51p2_read2.htm)

## References

- DeCarlo, L. T. (2011). On the analysis of fraction subtraction data: The DINA Model, classification, latent class sizes, and the Q-Matrix. *Applied Psychological Measurement*, *35*, 8–26.
- Tatsuoka, C. (2002). Data analytic methods for latent partially ordered classification models. *Journal of the Royal Statistical Society, Series C, Applied Statistics*, *51*, 337–350.
- Tatsuoka, K. (1984). *Analysis of errors in fraction addition and subtraction problems*. Final Report for NIE-G-81-0002, University of Illinois, Urbana-Champaign.

## See Also

[fraction.subtraction.qmatrix](#) for the corresponding Q-matrix.

---

fraction.subtraction.qmatrix  
*Fraction Subtraction Q-Matrix*

---

## Description

The Q-Matrix corresponding to Tatsuoka (1984) fraction subtraction data set.

## Usage

```
data(fraction.subtraction.qmatrix)
```

## Format

The `fraction.subtraction.qmatrix` data frame consists of  $J = 20$  rows and  $K = 8$  columns, specifying the attributes that are believed to be involved in solving the items. Each row in the data frame represents an item and the entries in the row indicate whether an attribute is needed to master the item (denoted by a "1") or not (denoted by a "0"). The attributes for the fraction subtraction data set are the following:

- alpha1 convert a whole number to a fraction,
- alpha2 separate a whole number from a fraction,
- alpha3 simplify before subtracting,
- alpha4 find a common denominator,
- alpha5 borrow from whole number part,
- alpha6 column borrow to subtract the second numerator from the first,
- alpha7 subtract numerators,
- alpha8 reduce answers to simplest form.

## Details

This Q-matrix can be found in DeCarlo (2011). It is the same used by de la Torre and Douglas (2004).

**Source**

DeCarlo, L. T. (2011). On the analysis of fraction subtraction data: The DINA Model, classification, latent class sizes, and the Q-Matrix. *Applied Psychological Measurement*, **35**, 8–26.

**References**

de la Torre, J. and Douglas, J. (2004). Higher-order latent trait models for cognitive diagnosis. *Psychometrika*, *69*, 333–353.

Tatsuoka, C. (2002). Data analytic methods for latent partially ordered classification models. *Journal of the Royal Statistical Society, Series C, Applied Statistics*, *51*, 337–350.

Tatsuoka, K. (1984) *Analysis of errors in fraction addition and subtraction problems*. Final Report for NIE-G-81-0002, University of Illinois, Urbana-Champaign.

gdd

*Generalized Distance Discriminating Method***Description**

Performs the generalized distance discriminating method (GDD; Sun, Xin, Zhang, & de la Torre, 2013) for dichotomous data which is a method for classifying students into skill profiles based on a preliminary unidimensional calibration.

**Usage**

```
gdd(data, q.matrix, theta, b, a, skillclasses=NULL)
```

**Arguments**

data	Data frame with $N \times J$ item responses
q.matrix	The Q-matrix
theta	Estimated person ability
b	Estimated item intercept from a 2PL model (see Details)
a	Estimated item slope from a 2PL model (see Details)
skillclasses	Optional matrix of skill classes used for estimation

**Details**

Note that the parameters in the arguments follow the item response model

$$\text{logit}P(X_{nj} = 1|\theta_n) = b_j + a_j\theta_n$$

which is employed in the `gdm` function.

**Value**

A list with following entries

skillclass.est	Estimated skill class
distmatrix	Distances for every person and every skill class
skillspace	Used skill space for estimation
theta	Used person parameter estimate

**References**

Sun, J., Xin, T., Zhang, S., & de la Torre, J. (2013). A polytomous extension of the generalized distance discriminating method. *Applied Psychological Measurement*, 37, 503-521.

**Examples**

```
#####
# EXAMPLE 1: GDD for sim.dina
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

data <- sim.dina
q.matrix <- sim.qmatrix

# estimate 1PL (use irtmodel="2PL" for 2PL estimation)
mod <- CDM::gdm( data, irtmodel="1PL", theta.k=seq(-6,6,len=21),
                decrease.increments=TRUE, conv=.001, globconv=.001)
# extract item parameters in parametrization b + a*theta
b <- mod$b[,1]
a <- mod$a[,1]
# extract person parameter estimate
theta <- mod$person$EAP.F1

# generalized distance discriminating method
res <- CDM::gdd( data, q.matrix, theta=theta, b=b, a=a )
```

---

 gdina

---

*Estimating the Generalized DINA (GDINA) Model*


---

**Description**

This function implements the generalized DINA model for dichotomous attributes (GDINA; de la Torre, 2011) and polytomous attributes (pGDINA; Chen & de la Torre, 2013, 2018). In addition, multiple group estimation is also possible using the `gdina` function. This function also allows for the estimation of a higher order GDINA model (de la Torre & Douglas, 2004). Polytomous item responses are treated by specifying a sequential GDINA model (Ma & de la Torre, 2016; Tutz,

1997). The simultaneous modeling of skills and misconceptions (bugs) can be also estimated within the GDINA framework (see Kuo, Chen & de la Torre, 2018; see argument rule).

The estimation can also be conducted by posing monotonicity constraints (Hong, Chang, & Tsai, 2016) using the argument `mono.constr`. Moreover, regularization methods SCAD, lasso, ridge, SCAD-L2 and truncated  $L_1$  penalty (TLP) for item parameters can be employed (Xu & Shang, 2018).

Normally distributed priors can be specified for item parameters (item intercepts and item slopes). Note that (for convenience) the prior specification holds simultaneously for all items.

### Usage

```
gdina(data, q.matrix, skillclasses=NULL, conv.crit=0.0001, dev.crit=.1, maxit=1000,
      linkfct="identity", Mj=NULL, group=NULL, invariance=TRUE, method=NULL,
      delta.init=NULL, delta.fixed=NULL, delta.designmatrix=NULL,
      delta.basispar.lower=NULL, delta.basispar.upper=NULL, delta.basispar.init=NULL,
      zeroprob.skillclasses=NULL, attr.prob.init=NULL, attr.prob.fixed=NULL,
      reduced.skillspace=NULL, reduced.skillspace.method=2, HOGDINA=-1, Z.skillspace=NULL,
      weights=rep(1, nrow(data)), rule="GDINA", bugs=NULL, regular_lam=0,
      regular_type="none", regular_alpha=NA, regular_tau=NA, regular_weights=NULL,
      mono.constr=FALSE, prior_intercepts=NULL, prior_slopes=NULL, progress=TRUE,
      progress.item=FALSE, mstep_iter=10, mstep_conv=1E-4, increment.factor=1.01,
      fac.oldxsi=0, max.increment=.3, avoid.zeroprob=FALSE, seed=0,
      save.devmin=TRUE, calc.se=TRUE, se_version=1, PEM=TRUE, PEM_itermax=maxit,
      cd=FALSE, cd_steps=1, mono_maxiter=10, freq_weights=FALSE, optimizer="CDM", ...)

## S3 method for class 'gdina'
summary(object, digits=4, file=NULL, ...)

## S3 method for class 'gdina'
plot(x, ask=FALSE, ...)

## S3 method for class 'gdina'
print(x, ...)
```

### Arguments

<code>data</code>	A required $N \times J$ data matrix containing integer responses, 0, 1, ..., K. Polytomous item responses are treated by the sequential GDINA model. NA values are allowed.
<code>q.matrix</code>	A required integer $J \times K$ matrix containing attributes not required or required, 0 or 1, to master the items in case of dichotomous attributes or integers in case of polytomous attributes. For polytomous item responses the Q-matrix must also include the item name and item category, see Example 11.
<code>skillclasses</code>	An optional matrix for determining the skill space. The argument can be used if a user wants less than $2^K$ skill classes.
<code>conv.crit</code>	Convergence criterion for maximum absolute change in item parameters
<code>dev.crit</code>	Convergence criterion for maximum absolute change in deviance

<code>maxit</code>	Maximum number of iterations
<code>linkfct</code>	A string which indicates the link function for the GDINA model. Options are "identity" (identity link), "logit" (logit link) and "log" (log link). The default is the "identity" link. Note that the link function is chosen for the whole model (i.e. for all items).
<code>Mj</code>	A list of design matrices and labels for each item. The definition of <code>Mj</code> follows the definition of $M_j$ in de la Torre (2011). Please study the value <code>Mj</code> of the function in default analysis. See Example 3.
<code>group</code>	A vector of group identifiers for multiple group estimation. Default is NULL (no multiple group estimation).
<code>invariance</code>	Logical indicating whether invariance of item parameters is assumed for multiple group models. If a subset of items should be treated as noninvariant, then invariance can be a vector of item names.
<code>method</code>	Estimation method for item parameters (see) (de la Torre, 2011). The default "WLS" weights probabilities attribute classes by a weighting matrix $W_j$ of expected frequencies, whereas the method "ULS" perform unweighted least squares estimation on expected frequencies. The method "ML" directly maximizes the log-likelihood function. The "ML" method is a bit slower but can be much more stable, especially in the case of the RRUM model. Only for the RRUM model, the default is changed to <code>method="ML"</code> if not specified otherwise.
<code>delta.init</code>	List with initial $\delta$ parameters
<code>delta.fixed</code>	List with fixed $\delta$ parameters. For free estimated parameters NA must be declared.
<code>delta.designmatrix</code>	A design matrix for restrictions on delta. See Example 4.
<code>delta.basispar.lower</code>	Lower bounds for delta basis parameters.
<code>delta.basispar.upper</code>	Upper bounds for delta basis parameters.
<code>delta.basispar.init</code>	An optional vector of starting values for the basis parameters of delta. This argument only applies when using a <code>designmatrix</code> for delta, i.e. <code>delta.designmatrix</code> is not NULL.
<code>zeroprob.skillclasses</code>	An optional vector of integers which indicates which skill classes should have zero probability. Default is NULL (no skill classes with zero probability).
<code>attr.prob.init</code>	Initial probabilities of skill distribution.
<code>attr.prob.fixed</code>	Vector or matrix with fixed probabilities of skill distribution.
<code>reduced.skillspace</code>	A logical which indicates if the latent class skill space dimension should be reduced (see Xu & von Davier, 2008). The default is NULL which applies skill space reduction for more than four skills. The dimensional reduction is only well defined for more than three skills. If the argument <code>zeroprob.skillclasses</code> is not NULL, then <code>reduced.skillspace</code> is set to FALSE.

<code>reduced.skillspace.method</code>	Computation method for skill space reduction in case of <code>reduced.skillspace=TRUE</code> . The default is 2 which is computationally more efficient but introduced in <b>CDM</b> 2.6. For reasons of compatibility of former <b>CDM</b> versions ( $\leq 2.5$ ), <code>reduced.skillspace.method=1</code> uses the older implemented method. In case of non-convergence with the new method, please try the older method.
<code>HOGDINA</code>	Values of -1, 0 or 1 indicating if a higher order GDINA model (see Details) should be estimated. The default value of -1 corresponds to the case that no higher order factor is assumed to exist. A value of 0 corresponds to independent attributes. A value of 1 assumes the existence of a higher order factor.
<code>Z.skillspace</code>	A user specified design matrix for the skill space reduction as described in Xu and von Davier (2008). See in the Examples section for applications. See Example 6.
<code>weights</code>	An optional vector of sample weights.
<code>rule</code>	A string or a vector of itemwise condensation rules. Allowed entries are GDINA, DINA, DINO, ACDM (additive cognitive diagnostic model) and RRUM (reduced reparametrized unified model, RRUM, see Details). The rule GDINA1 applies only main effects in the GDINA model which is equivalent to ACDM. The rule GDINA2 applies to all main effects and second-order interactions of the attributes. If some item is specified as RRUM, then for all the items the reduced RUM will be estimated which means that the log link function and the ACDM condensation rule is used. In the output, the entry <code>rrum.params</code> contains the parameters transformed in the RUM parametrization. If <code>rule</code> is a string, the condensation rule applies to all items. If <code>rule</code> is a vector, condensation rules can be specified itemwise. The default is GDINA for all items.
<code>bugs</code>	Character vector indicating which columns in the Q-matrix refer to bugs (misconceptions). This is only available if some <code>rule</code> is set to "SISM". Note that bugs must be included as last columns in the Q-matrix.
<code>regular_lam</code>	Regularization parameter $\lambda$
<code>regular_type</code>	Type of regularization. Can be <code>scad</code> (SCAD penalty), <code>lasso</code> (lasso penalty), <code>ridge</code> (ridge penalty), <code>elnet</code> (elastic net), <code>scadL2</code> (SCAD- $L_2$ ; Zeng & Xie, 2014), <code>t1p</code> (truncated $L_1$ penalty; Xu & Shang, 2018; Shen, Pan, & Zhu, 2012), <code>mcp</code> (MCP penalty; Zhang, 2010) or <code>none</code> (no regularization).
<code>regular_alpha</code>	Regularization parameter $\alpha$ (applicable for elastic net or SCAD-L2).
<code>regular_tau</code>	Regularization parameter $\tau$ for truncated $L_1$ penalty.
<code>regular_weights</code>	Optional list of item parameter weights used for penalties in regularized estimation (see Example 13)
<code>mono.constr</code>	Logical indicating whether monotonicity constraints should be fulfilled in estimation (implemented by the increasing penalty method; see Nash, 2014, p. 156).
<code>prior_intercepts</code>	Vector with mean and standard deviation for prior of random intercepts (applies to all items)
<code>prior_slopes</code>	Vector with mean and standard deviation for prior of random slopes (applies to all items and all parameters)

<code>progress</code>	An optional logical indicating whether the function should print the progress of iteration in the estimation process.
<code>progress.item</code>	An optional logical indicating whether item wise progress should be displayed
<code>mstep_iter</code>	Number of iterations in M-step if method="ML".
<code>mstep_conv</code>	Convergence criterion in M-step if method="ML".
<code>increment.factor</code>	A factor larger than 1 (say 1.1) to control maximum increments in item parameters. This parameter can be used in case of nonconvergence.
<code>fac.oldxsi</code>	A convergence acceleration factor between 0 and 1 which defines the weight of previously estimated values in current parameter updates.
<code>max.increment</code>	Maximum size of change in increments in M steps of EM algorithm when method="ML" is used.
<code>avoid.zeroprobs</code>	An optional logical indicating whether for estimating item parameters probabilities occur. Especially if not a skill classes are used, it is recommended to switch the argument to TRUE.
<code>seed</code>	Simulation seed for initial parameters. A value of zero corresponds to deterministic starting values, an integer value different from zero to random initial values with <code>set.seed(seed)</code> .
<code>save.devmin</code>	An optional logical indicating whether intermediate estimates should be saved corresponding to minimal deviance. Setting the argument to FALSE could help for preventing working memory overflow.
<code>calc.se</code>	Optional logical indicating whether standard errors should be calculated.
<code>se_version</code>	Integer for calculation method of standard errors. <code>se_version=1</code> is based on the observed log likelihood and included since <b>CDM</b> 5.1 and is the default. Comparability with previous <b>CDM</b> versions can be obtained with <code>se_version=0</code> .
<code>PEM</code>	Logical indicating whether the P-EM acceleration should be applied (Berliner & Roland, 2012).
<code>PEM_itermax</code>	Number of iterations in which the P-EM method should be applied.
<code>cd</code>	Logical indicating whether coordinate descent algorithm should be used.
<code>cd_steps</code>	Number of steps for each parameter in coordinate descent algorithm
<code>mono_maxiter</code>	Maximum number of iterations for fulfilling the monotonicity constraint
<code>freq_weights</code>	Logical indicating whether frequency weights should be used. Default is FALSE.
<code>optimizer</code>	String indicating which optimizer should be used in M-step estimation in case of method="ML". The internal optimizer of <b>CDM</b> can be requested by <code>optimizer="CDM"</code> . The optimization with <code>stats::optim</code> can be requested by <code>optimizer="optim"</code> . For the RRUM model, it is always chosen <code>optimizer="optim"</code> .
<code>object</code>	A required object of class <code>gdina</code> , obtained from a call to the function <code>gdina</code> .
<code>digits</code>	Number of digits after decimal separator to display.
<code>file</code>	Optional file name for a file in which summary should be sinked.
<code>x</code>	A required object of class <code>gdina</code>
<code>ask</code>	A logical indicating whether every separate item should be displayed in <code>plot.gdina</code>
<code>...</code>	Optional parameters to be passed to or from other methods will be ignored.



## Details

The estimation is based on an EM algorithm as described in de la Torre (2011). Item parameters are contained in the `delta` vector which is a list where the  $j$ th entry corresponds to item parameters of the  $j$ th item.

The following description refers to the case of dichotomous attributes. For using polytomous attributes see Chen and de la Torre (2013) and Example 7 for a definition of the Q-matrix. In this case,  $Q_{ik} = l$  means that the  $i$ th item requires the mastery (at least) of level  $l$  of attribute  $k$ .

Assume that two skills  $\alpha_1$  and  $\alpha_2$  are required for mastering item  $j$ . Then the GDINA model can be written as

$$g[P(X_{nj} = 1|\alpha_n)] = \delta_{j0} + \delta_{j1}\alpha_{n1} + \delta_{j2}\alpha_{n2} + \delta_{j12}\alpha_{n1}\alpha_{n2}$$

which is a two-way GDINA-model (the `rule="GDINA2"` specification) with a link function  $g$  (which can be the identity, logit or logarithmic link). If the specification ACDM is chosen, then  $\delta_{j12} = 0$ . The DINA model (`rule="DINA"`) assumes  $\delta_{j1} = \delta_{j2} = 0$ .

For the reduced RUM model (`rule="RRUM"`), the item response model is

$$P(X_{nj} = 1|\alpha_n) = \pi_i^* \cdot r_{i1}^{1-\alpha_{i1}} \cdot r_{i2}^{1-\alpha_{i2}}$$

From this equation, it is obvious, that this model is equivalent to an additive model (`rule="ACDM"`) with a logarithmic link function (`linkfct="log"`).

If a reduced skillspace (`reduced.skillspace=TRUE`) is employed, then the logarithm of probability distribution of the attributes is modeled as a log-linear model:

$$\log P[(\alpha_{n1}, \alpha_{n2}, \dots, \alpha_{nK})] = \gamma_0 + \sum_k \gamma_k \alpha_{nk} + \sum_{k < l} \gamma_{kl} \alpha_{nk} \alpha_{nl}$$

If a higher order DINA model is assumed (`HOGDINA=1`), then a higher order factor  $\theta_n$  for the attributes is assumed:

$$P(\alpha_{nk} = 1|\theta_n) = \Phi(a_k \theta_n + b_k)$$

For `HOGDINA=0`, all attributes  $\alpha_{nk}$  are assumed to be independent of each other:

$$P[(\alpha_{n1}, \alpha_{n2}, \dots, \alpha_{nK})] = \prod_k P(\alpha_{nk})$$

Note that the noncompensatory reduced RUM (NC-RRUM) according to Rupp and Templin (2008) is the GDINA model with the arguments `rule="ACDM"` and `linkfct="log"`. NC-RRUM can also be obtained by choosing `rule="RRUM"`.

The compensatory RUM (C-RRUM) can be obtained by using the arguments `rule="ACDM"` and `linkfct="logit"`.

The cognitive diagnosis model for identifying skills and misconceptions (SISM; Kuo, Chen & de la Torre, 2018) can be estimated with `rule="SISM"` (see Example 12).

The `gdina` function internally parameterizes the GDINA model as

$$g[P(X_{nj} = 1|\alpha_n)] = M_j(\alpha_n)\delta_j$$

with item-specific design matrices  $M_j(\alpha_n)$  and item parameters  $\delta_j$ . Only those attributes are modelled which correspond to non-zero entries in the Q-matrix. Because the Q-matrix (in `q.matrix`) and the design matrices (in `M_j`; see Example 3) can be specified by the user, several cognitive diagnosis models can be estimated. Therefore, some additional extensions of the DINA model can also be estimated using the `gdina` function. These models include the DINA model with multiple strategies (Huo & de la Torre, 2014)

**Value**

An object of class `gdina` with following entries

<code>coef</code>	Data frame of item parameters
<code>delta</code>	List with basis item parameters
<code>se.delta</code>	Standard errors of basis item parameters
<code>probitem</code>	Data frame with model implied conditional item probabilities $P(X_i = 1 \alpha)$ . These probabilities are displayed in <code>plot.gdina</code> .
<code>itemfit.rmsea</code>	The RMSEA item fit index (see <code>itemfit.rmsea</code> ).
<code>mean.rmsea</code>	Mean of RMSEA item fit indexes.
<code>loglike</code>	Log-likelihood
<code>deviance</code>	Deviance
<code>G</code>	Number of groups
<code>N</code>	Sample size
<code>AIC</code>	AIC
<code>BIC</code>	BIC
<code>CAIC</code>	CAIC
<code>Npars</code>	Total number of parameters
<code>Nipar</code>	Number of item parameters
<code>Nskillpar</code>	Number of parameters for skill class distribution
<code>Nskillclasses</code>	Number of skill classes
<code>varmat.delta</code>	Covariance matrix of $\delta$ item parameters
<code>posterior</code>	Individual posterior distribution
<code>like</code>	Individual likelihood
<code>data</code>	Original data
<code>q.matrix</code>	Used Q-matrix
<code>pattern</code>	Individual patterns, individual MLE and MAP classifications and their corresponding probabilities
<code>attribute.patt</code>	Probabilities of skill classes
<code>skill.patt</code>	Marginal skill probabilities
<code>subj.pattern</code>	Individual subject pattern
<code>attribute.patt.splitted</code>	Splitted attribute pattern
<code>pjk</code>	Array of item response probabilities
<code>Mj</code>	Design matrix $M_j$ in GDINA algorithm (see de la Torre, 2011)
<code>Aj</code>	Design matrix $A_j$ in GDINA algorithm (see de la Torre, 2011)
<code>rule</code>	Used condensation rules
<code>linkfct</code>	Used link function

<code>delta.designmatrix</code>	Designmatrix for item parameters
<code>reduced.skillspace</code>	A logical if skillspace reduction was performed
<code>Z.skillspace</code>	Design matrix for skillspace reduction
<code>beta</code>	Parameters $\delta$ for skill class representation
<code>covbeta</code>	Standard errors of $\delta$ parameters
<code>iter</code>	Number of iterations
<code>rrum.params</code>	Parameters in the parametrization of the reduced RUM model if rule="RRUM".
<code>group.stat</code>	Group statistics (sample sizes, group labels)
<code>HOGDINA</code>	The used value of HOGDINA
<code>mono.constr</code>	Monotonicity constraint
<code>regularization</code>	Logical indicating whether regularization is used
<code>regular_lam</code>	Regularization parameter
<code>numb_bound_mono</code>	Number of items with parameters at boundary of monotonicity constraints
<code>numb_regular_pars</code>	Number of regularized item parameters
<code>delta_regularized</code>	List indicating which item parameters are regularized
<code>cd_algorithm</code>	Logical indicating whether coordinate descent algorithm is used
<code>cd_steps</code>	Number of steps for each parameter in coordinate descent algorithm
<code>seed</code>	Used simulation seed
<code>a.attr</code>	Attribute parameters $a_k$ in case of HOGDINA>=0
<code>b.attr</code>	Attribute parameters $b_k$ in case of HOGDINA>=0
<code>attr.rf</code>	Attribute response functions. This matrix contains all $a_k$ and $b_k$ parameters
<code>converged</code>	Logical indicating whether convergence was achieved.
<code>control</code>	Optimization parameters used in estimation
<code>partable</code>	Parameter table for gdina function
<code>polychor</code>	Group-wise matrices with polychoric correlations
<code>sequential</code>	Logical indicating whether a sequential GDINA model is applied for polytomous item responses
<code>...</code>	Further values

### Note

The function `din` does not allow for multiple group estimation. Use this `gdina` function instead and choose the appropriate rule="DINA" as an argument.

Standard error calculation in analyses which use sample weights or designmatrix for delta parameters (`delta.designmatrix!=NULL`) is not yet correctly implemented. Please use replication methods instead.

## References

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## See Also

- See also the [din](#) function (for DINA and DINO estimation).
- For assessment of model fit see [modelfit.cor.din](#) and [anova.gdina](#).
- See [itemfit.sx2](#) for item fit statistics.
- See [sim.gdina](#) for simulating the GDINA model.
- See [gdina.wald](#) for a Wald test for testing the DINA and ACDM rules at the item-level.

See `gdina.dif` for assessing differential item functioning.

See `discrim.index` for computing discrimination indices.

See the `GDINA::GDINA` function in the **GDINA** package for similar functionality.

## Examples

```
#####
# EXAMPLE 1: Simulated DINA data | different condensation rules
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

dat <- sim.dina
Q <- sim.qmatrix

###
# Model 1: estimation of the GDINA model (identity link)
mod1 <- CDM::gdina( data=dat, q.matrix=Q)
summary(mod1)
plot(mod1) # apply plot function

## Not run:
# Model 1a: estimate model with different simulation seed
mod1a <- CDM::gdina( data=dat, q.matrix=Q, seed=9089)
summary(mod1a)

# Model 1b: estimate model with some fixed delta parameters
delta.fixed <- as.list( rep(NA,9) ) # List for parameters of 9 items
delta.fixed[[2]] <- c( 0, .15, .15, .45 )
delta.fixed[[6]] <- c( .25, .25 )
mod1b <- CDM::gdina( data=dat, q.matrix=Q, delta.fixed=delta.fixed)
summary(mod1b)

# Model 1c: fix all delta parameters to previously fitted model
mod1c <- CDM::gdina( data=dat, q.matrix=Q, delta.fixed=mod1$delta)
summary(mod1c)

# Model 1d: estimate GDINA model with GDINA package
mod1d <- GDINA::GDINA( dat=dat, Q=Q, model="GDINA" )
summary(mod1d)
# extract item parameters
GDINA::itemparm(mod1d)
GDINA::itemparm(mod1d, what="delta")
# compare likelihood
logLik(mod1)
logLik(mod1d)

###
# Model 2: estimation of the DINA model with gdina function
mod2 <- CDM::gdina( data=dat, q.matrix=Q, rule="DINA")
summary(mod2)
```

```
plot(mod2)

####
# Model 2b: compare results with din function
mod2b <- CDM::din( data=dat, q.matrix=Q, rule="DINA")
summary(mod2b)

# Model 2: estimation of the DINO model with gdina function
mod3 <- CDM::gdina( data=dat, q.matrix=Q, rule="DINO")
summary(mod3)

####
# Model 4: DINA model with logit link
mod4 <- CDM::gdina( data=dat, q.matrix=Q, rule="DINA", linkfct="logit" )
summary(mod4)

####
# Model 5: DINA model log link
mod5 <- CDM::gdina( data=dat, q.matrix=Q, rule="DINA", linkfct="log")
summary(mod5)

####
# Model 6: RRUM model
mod6 <- CDM::gdina( data=dat, q.matrix=Q, rule="RRUM")
summary(mod6)

####
# Model 7: Higher order GDINA model
mod7 <- CDM::gdina( data=dat, q.matrix=Q, HOGDINA=1)
summary(mod7)

####
# Model 8: GDINA model with independent attributes
mod8 <- CDM::gdina( data=dat, q.matrix=Q, HOGDINA=0)
summary(mod8)

####
# Model 9: Estimating the GDINA model with monotonicity constraints
mod9 <- CDM::gdina( data=dat, q.matrix=Q, rule="GDINA",
                    mono.constr=TRUE, linkfct="logit")
summary(mod9)

####
# Model 10: Estimating the ACDM model with SCAD penalty and regularization
#           parameter of .05
mod10 <- CDM::gdina( data=dat, q.matrix=Q, rule="ACDM",
                    linkfct="logit", regular_type="scad", regular_lam=.05 )
summary(mod10)

####
# Model 11: Estimation of GDINA model with prior distributions
# N(0,10^2) prior for item intercepts
```

```

prior_intercepts <- c(0,10)
# N(0,1^2) prior for item slopes
prior_slopes <- c(0,1)
# estimate model
mod11 <- CDM::gdina( data=dat, q.matrix=Q, rule="GDINA",
                    prior_intercepts=prior_intercepts, prior_slopes=prior_slopes)
summary(mod11)

#####
# EXAMPLE 2: Simulated DINO data
# additive cognitive diagnosis model with different link functions
#####

data(sim.dino, package="CDM")
data(sim.matrix, package="CDM")

dat <- sim.dino
Q <- sim.qmatrix

###
# Model 1: additive cognitive diagnosis model (ACDM; identity link)
mod1 <- CDM::gdina( data=dat, q.matrix=Q, rule="ACDM")
summary(mod1)

###
# Model 2: ACDM logit link
mod2 <- CDM::gdina( data=dat, q.matrix=Q, rule="ACDM", linkfct="logit")
summary(mod2)

###
# Model 3: ACDM log link
mod3 <- CDM::gdina( data=dat, q.matrix=Q, rule="ACDM", linkfct="log")
summary(mod3)

###
# Model 4: Different condensation rules per item
I <- 9 # number of items
rule <- rep( "GDINA", I )
rule[1] <- "DINO" # 1st item: DINO model
rule[7] <- "GDINA2" # 7th item: GDINA model with first- and second-order interactions
rule[8] <- "ACDM" # 8th item: additive CDM
rule[9] <- "DINA" # 9th item: DINA model
mod4 <- CDM::gdina( data=dat, q.matrix=Q, rule=rule )
summary(mod4)

#####
# EXAMPLE 3: Model with user-specified design matrices
#####

data(sim.dino, package="CDM")
data(sim.qmatrix, package="CDM")

dat <- sim.dino

```

```

Q <- sim.qmatrix

# do a preliminary analysis and modify obtained design matrices
mod0 <- CDM::gdina( data=dat, q.matrix=Q, maxit=1)

# extract default design matrices
Mj <- mod0$Mj
Mj.user <- Mj # these user defined design matrices are modified.
#~~~ For the second item, the following model should hold
# X1 ~ V2 + V2*V3
mj <- Mj[[2]][[1]]
mj.lab <- Mj[[2]][[2]]
mj <- mj[,-3]
mj.lab <- mj.lab[-3]
Mj.user[[2]] <- list( mj, mj.lab )
# [[1]]
# [ ,1] [ ,2] [ ,3]
# [1,] 1 0 0
# [2,] 1 1 0
# [3,] 1 0 0
# [4,] 1 1 1
# [[2]]
# [1] "0" "1" "1-2"
#~~~ For the eight item an equality constraint should hold
# X8 ~ a*V2 + a*V3 + V2*V3
mj <- Mj[[8]][[1]]
mj.lab <- Mj[[8]][[2]]
mj[,2] <- mj[,2] + mj[,3]
mj <- mj[,-3]
mj.lab <- c("0", "1=2", "1-2" )
Mj.user[[8]] <- list( mj, mj.lab )
Mj.user[[8]]
## [[1]]
## [ ,1] [ ,2] [ ,3]
## [1,] 1 0 0
## [2,] 1 1 0
## [3,] 1 1 0
## [4,] 1 2 1
##
## [[2]]
## [1] "0" "1=2" "1-2"
mod <- CDM::gdina( data=dat, q.matrix=Q,
                  Mj=Mj.user, maxit=200 )
summary(mod)

#####
# EXAMPLE 4: Design matrix for delta parameters
#####

data(sim.dino, package="CDM")
data(sim.qmatrix, package="CDM")

#~~~ estimate an initial model

```



```

mod0 <- CDM::gdina( data=dat, q.matrix=Q, rule="ACDM", maxit=1)
# extract coefficients
c0 <- mod0$coef
I <- 9 # number of items
delta.designmatrix <- matrix( 0, nrow=nrow(c0), ncol=nrow(c0) )
diag( delta.designmatrix) <- 1
# set intercept of item 1 and item 3 equal to each other
delta.designmatrix[ 7, 1 ] <- 1 ; delta.designmatrix[,7] <- 0
# set loading of V1 of item1 and item 3 equal
delta.designmatrix[ 8, 2 ] <- 1 ; delta.designmatrix[,8] <- 0
delta.designmatrix <- delta.designmatrix[, -c(7:8) ]
# exclude original parameters with indices 7 and 8

####
# Model 1: ACDM with designmatrix
mod1 <- CDM::gdina( data=dat, q.matrix=Q, rule="ACDM",
  delta.designmatrix=delta.designmatrix )
summary(mod1)

####
# Model 2: Same model, but with logit link instead of identity link function
mod2 <- CDM::gdina( data=dat, q.matrix=Q, rule="ACDM",
  delta.designmatrix=delta.designmatrix, linkfct="logit")
summary(mod2)

#####
# EXAMPLE 5: Multiple group estimation
#####

# simulate data
set.seed(9279)
N1 <- 200 ; N2 <- 100 # group sizes
I <- 10 # number of items
q.matrix <- matrix(0,I,2) # create Q-matrix
q.matrix[1:7,1] <- 1 ; q.matrix[ 5:10,2] <- 1
# simulate first group
dat1 <- CDM::sim.din(N1, q.matrix=q.matrix, mean=c(0,0) )$dat
# simulate second group
dat2 <- CDM::sim.din(N2, q.matrix=q.matrix, mean=c(-.3, -.7) )$dat
# merge data
dat <- rbind( dat1, dat2 )
# group indicator
group <- c( rep(1,N1), rep(2,N2) )

# estimate GDINA model with multiple groups assuming invariant item parameters
mod1 <- CDM::gdina( data=dat, q.matrix=q.matrix, group=group)
summary(mod1)

# estimate DINA model with multiple groups assuming invariant item parameters
mod2 <- CDM::gdina( data=dat, q.matrix=q.matrix, group=group, rule="DINA")
summary(mod2)

# estimate GDINA model with noninvariant item parameters

```

```

mod3 <- CDM::gdina( data=dat, q.matrix=q.matrix, group=group, invariance=FALSE)
summary(mod3)

# estimate GDINA model with some invariant item parameters (I001, I006, I008)
mod4 <- CDM::gdina( data=dat, q.matrix=q.matrix, group=group,
  invariance=c("I001", "I006","I008") )

#--- model comparison
IRT.compareModels(mod1,mod2,mod3,mod4)

# estimate GDINA model with non-invariant item parameters except for the
# items I001, I006, I008
mod5 <- CDM::gdina( data=dat, q.matrix=q.matrix, group=group,
  invariance=setdiff( colnames(dat), c("I001", "I006","I008") ) )

#####
# EXAMPLE 6: User specified reduced skill space
#####

# Some correlations between attributes should be set to zero.
q.matrix <- expand.grid( c(0,1), c(0,1), c(0,1), c(0,1) )
colnames(q.matrix) <- colnames( paste("Attr", 1:4,sep=""))
q.matrix <- q.matrix[ -1, ]
Sigma <- matrix( .5, nrow=4, ncol=4 )
diag(Sigma) <- 1
Sigma[3,2] <- Sigma[2,3] <- 0 # set correlation of attribute A2 and A3 to zero
dat <- CDM::sim.din( N=1000, q.matrix=q.matrix, Sigma=Sigma)$dat

#~~~ Step 1: initial estimation
mod1a <- CDM::gdina( data=dat, q.matrix=q.matrix, maxit=1, rule="DINA")
# estimate also "full" model
mod1 <- CDM::gdina( data=dat, q.matrix=q.matrix, rule="DINA")

#~~~ Step 2: modify designmatrix for reduced skill space
Z.skillspace <- data.frame( mod1a$Z.skillspace )
# set correlations of A2/A4 and A3/A4 to zero
vars <- c("A2_A3","A2_A4")
for (vv in vars){ Z.skillspace[,vv] <- NULL }

#~~~ Step 3: estimate model with reduced skill space
mod2 <- CDM::gdina( data=dat, q.matrix=q.matrix,
  Z.skillspace=Z.skillspace, rule="DINA")

#~~~ eliminate all covariances
Z.skillspace <- data.frame( mod1$Z.skillspace )
colnames(Z.skillspace)
Z.skillspace <- Z.skillspace[, -grep( "_", colnames(Z.skillspace),fixed=TRUE)]
colnames(Z.skillspace)

mod3 <- CDM::gdina( data=dat, q.matrix=q.matrix,
  Z.skillspace=Z.skillspace, rule="DINA")
summary(mod1)
summary(mod2)

```

```

summary(mod3)

#####
# EXAMPLE 7: Polytomous GDINA model (Chen & de la Torre, 2013)
#####

data(data.pgdina, package="CDM")

dat <- data.pgdina$dat
q.matrix <- data.pgdina$q.matrix

# pGDINA model with "DINA rule"
mod1 <- CDM::gdina( dat, q.matrix=q.matrix, rule="DINA")
summary(mod1)
# no reduced skill space
mod1a <- CDM::gdina( dat, q.matrix=q.matrix, rule="DINA", reduced.skillspace=FALSE)
summary(mod1)

# pGDINA model with "GDINA rule"
mod2 <- CDM::gdina( dat, q.matrix=q.matrix, rule="GDINA")
summary(mod2)

#####
# EXAMPLE 8: Fraction subtraction data: DINA and HO-DINA model
#####

data(fraction.subtraction.data, package="CDM")
data(fraction.subtraction.qmatrix, package="CDM")

dat <- fraction.subtraction.data
Q <- fraction.subtraction.qmatrix

# Model 1: DINA model
mod1 <- CDM::gdina( dat, q.matrix=Q, rule="DINA")
summary(mod1)

# Model 2: HO-DINA model
mod2 <- CDM::gdina( dat, q.matrix=Q, HOGDINA=1, rule="DINA")
summary(mod2)

#####
# EXAMPLE 9: Skill space approximation data.jang
#####

data(data.jang, package="CDM")

data <- data.jang$data
q.matrix <- data.jang$q.matrix

#*** Model 1: Reduced RUM model
mod1 <- CDM::gdina( data, q.matrix, rule="RRUM", conv.crit=.001, maxit=500 )

#*** Model 2: Reduced RUM model with skill space approximation

```

```

# use 300 instead of 2^9=512 skill classes
skillspace <- CDM::skillspace.approximation( L=300, K=ncol(q.matrix) )
mod2 <- CDM::gdina( data, q.matrix, rule="RRUM", conv.crit=.001,
  skillclasses=skillspace )
## > logLik(mod1)
## 'log Lik.' -30318.08 (df=153)
## > logLik(mod2)
## 'log Lik.' -30326.52 (df=153)

#####
# EXAMPLE 10: CDM with a linear hierarchy
#####
# This model is equivalent to a unidimensional IRT model with an ordered
# ordinal latent trait and is actually a probabilistic Guttman model.
set.seed(789)

# define 3 competency levels
alpha <- scan()
  0 0 0  1 0 0  1 1 0  1 1 1

# define skill class distribution
K <- 3
skillspace <- alpha <- matrix( alpha, K + 1, K, byrow=TRUE )
alpha <- alpha[ rep( 1:4, c(300,300,200,200) ), ]
# P(000)=P(100)=.3, P(110)=P(111)=.2
# define Q-matrix
Q <- scan()
  1 0 0  1 1 0  1 1 1

Q <- matrix( Q, nrow=K, ncol=K, byrow=TRUE )
Q <- Q[ rep(1:K, each=4 ), ]
colnames(skillspace) <- colnames(Q) <- paste0("A",1:K)
I <- nrow(Q)

# define guessing and slipping parameters
guess <- stats::runif( I, 0, .3 )
slip <- stats::runif( I, 0, .2 )
# simulate data
dat <- CDM::sim.din( q.matrix=Q, alpha=alpha, slip=slip, guess=guess )$dat

#### Model 1: DINA model with linear hierarchy
mod1 <- CDM::din( dat, q.matrix=Q, rule="DINA", skillclasses=skillspace )
summary(mod1)

#### Model 2: pGDINA model with 3 levels
# The multidimensional CDM with a linear hierarchy is a unidimensional
# polytomous GDINA model.
Q2 <- matrix( rowSums(Q), nrow=I, ncol=1 )
mod2 <- CDM::gdina( dat, q.matrix=Q2, rule="DINA" )
summary(mod2)

#### Model 3: estimate probabilistic Guttman model in sirt
# Proctor, C. H. (1970). A probabilistic formulation and statistical

```

```

# analysis for Guttman scaling. Psychometrika, 35, 73-78.
library(sirt)
mod3 <- sirt::prob.guttman( dat, itemlevel=Q2[,1] )
summary(mod3)
# -> The three models result in nearly equivalent fit.

#####
# EXAMPLE 11: Sequential GDINA model (Ma & de la Torre, 2016)
#####

data(data.cdm04, package="CDM")

*** attach dataset
dat <- data.cdm04$data # polytomous item responses
q.matrix1 <- data.cdm04$q.matrix1
q.matrix2 <- data.cdm04$q.matrix2

#-- DINA model with first Q-matrix
mod1 <- CDM::gdina( dat, q.matrix=q.matrix1, rule="DINA")
summary(mod1)
#-- DINA model with second Q-matrix
mod2 <- CDM::gdina( dat, q.matrix=q.matrix2, rule="DINA")
#-- GDINA model
mod3 <- CDM::gdina( dat, q.matrix=q.matrix2, rule="GDINA")

*** model comparison
IRT.compareModels(mod1,mod2,mod3)

#####
# EXAMPLE 12: Simultaneous modeling of skills and misconceptions (Kuo et al., 2018)
#####

data(data.cdm08, package="CDM")
dat <- data.cdm08$data
q.matrix <- data.cdm08$q.matrix

*** estimate model
mod <- CDM::gdina( dat, q.matrix, rule="SISM", bugs=colnames(q.matrix)[5:7] )
summary(mod)

#####
# EXAMPLE 13: Regularized estimation in GDINA model data.dtmr
#####

data(data.dtmr, package="CDM")
dat <- data.dtmr$data
q.matrix <- data.dtmr$q.matrix

***** LASSO regularization with lambda parameter of .02
mod1 <- CDM::gdina(dat, q.matrix=q.matrix, rule="GDINA", regular_lam=.02,
                  regular_type="lasso")
summary(mod1)
mod1$delta_regularized

```

```

##### using starting values from previous estimation
delta.init <- mod1$delta
attr.prob.init <- mod1$attr.prob
mod2 <- CDM::gdina(dat, q.matrix=q.matrix, rule="GDINA", regular_lam=.02, regular_type="lasso",
                  delta.init=delta.init, attr.prob.init=attr.prob.init)
summary(mod2)

##### final estimation fixing regularized estimates to zero and estimate all other
##### item parameters unregularized
regular_weights <- mod2$delta_regularized
delta.init <- mod2$delta
attr.prob.init <- mod2$attr.prob

mod3 <- CDM::gdina(dat, q.matrix=q.matrix, rule="GDINA", regular_lam=1E5, regular_type="lasso",
                  delta.init=delta.init, attr.prob.init=attr.prob.init,
                  regular_weights=regular_weights)
summary(mod3)

## End(Not run)

```

---

gdina.dif

---

*Differential Item Functioning in the GDINA Model*


---

## Description

This function assesses item-wise differential item functioning in the GDINA model by using the Wald test (de la Torre, 2011; Hou, de la Torre & Nandakumar, 2014). It is necessary that a multiple group GDINA model is previously fitted.

## Usage

```

gdina.dif(object)

## S3 method for class 'gdina.dif'
summary(object, ...)

```

## Arguments

object	Object of class <code>gdina</code>
...	Further arguments to be passed

## Details

The p values are also calculated by a Holm adjustment for multiple comparisons (see `p.holm` in output `difstats`).

In the case of two groups, an effect size of differential item functioning (labeled as UA (unsigned area) in difstats value) is defined as the weighted absolute difference of item response functions. The DIF measure for item  $j$  is defined as

$$UA_j = \sum_l w(\alpha_l) |P(X_j = 1 | \alpha_l, G = 1) - P(X_j = 1 | \alpha_l, G = 2)|$$

where  $w(\alpha_l) = [P(\alpha_l | G = 1) + P(\alpha_l | G = 2)]/2$ .

## Value

A list with following entries

difstats	Data frame containing results of item-wise Wald tests
coef	Data frame containing all (group-wise) item parameters
delta_all	List of $\delta$ vectors containing all item parameters
varmat_all	List of covariance matrices of all $\delta$ item parameters
prob.exp.group	List with groups and items containing expected latent class sizes and expected probabilities for each group and each item. Based on this information, effect sizes of differential item functioning can be calculated.

## References

de la Torre, J. (2011). The generalized DINA model framework. *Psychometrika*, 76, 179-199.

Hou, L., de la Torre, J., & Nandakumar, R. (2014). Differential item functioning assessment in cognitive diagnostic modeling: Application of the Wald test to investigate DIF in the DINA model. *Journal of Educational Measurement*, 51, 98-125.

## See Also

See the `GDINA::dif` function in the **GDINA** package for similar functionality.

## Examples

```
## Not run:
#####
# EXAMPLE 1: DIF for DINA simulated data
#####

# simulate some data
set.seed(976)
N <- 2000 # number of persons in a group
I <- 9    # number of items
q.matrix <- matrix( 0, 9, 2 )
q.matrix[1:3,1] <- 1
q.matrix[4:6,2] <- 1
q.matrix[7:9,c(1,2)] <- 1
# simulate first group
guess <- rep( .2, I )
slip <- rep(.1, I)
```

```

dat1 <- CDM::sim.din( N=N, q.matrix=q.matrix, guess=guess, slip=slip,
                    mean=c(0,0) )$dat
# simulate second group with some DIF items (items 1, 7 and 8)
guess[ c(1,7)] <- c(.3, .35 )
slip[8] <- .25
dat2 <- CDM::sim.din( N=N, q.matrix=q.matrix, guess=guess, slip=slip,
                    mean=c(0.4,.25) )$dat
group <- rep(1:2, each=N )
dat <- rbind( dat1, dat2 )

### estimate multiple group GDINA model
mod1 <- CDM::gdina( dat, q.matrix=q.matrix, rule="DINA", group=group )
summary(mod1)

### assess differential item functioning
dmod1 <- CDM::gdina.dif( mod1)
summary(dmod1)
##      item      X2 df      p p.holm      UA
##  1 I001 10.1711  2 0.0062 0.0495 0.0428
##  2 I002  1.9933  2 0.3691 1.0000 0.0276
##  3 I003  0.0313  2 0.9845 1.0000 0.0040
##  4 I004  0.0290  2 0.9856 1.0000 0.0044
##  5 I005  2.3230  2 0.3130 1.0000 0.0142
##  6 I006  1.8330  2 0.3999 1.0000 0.0159
##  7 I007 40.6851  2 0.0000 0.0000 0.1184
##  8 I008  6.7912  2 0.0335 0.2346 0.0710
##  9 I009  1.1538  2 0.5616 1.0000 0.0180

## End(Not run)

```

---

gdina.wald

*Wald Statistic for Item Fit of the DINA and ACDM Rule for GDINA Model*

---

## Description

This function tests with a Wald test for the GDINA model whether a DINA or a ACDM condensation rule leads to a sufficient item fit compared to the saturated GDINA rule (de la Torre & Lee, 2013). The Wald test is accompanied by the RMSEA fit and weighted and unweighted distance measures (wgtdist, uwgtdist), see Details (compare Ma, Iaconangelo, & de la Torre, 2016).

## Usage

```

gdina.wald(object)

## S3 method for class 'gdina.wald'
summary(object, digits=3,
        vars=c("X2", "p", "sig", "RMSEA", "wgtdist"), ...)

```



**Arguments**

object	A fitted <code>gdina</code> model
digits	Number of digits after decimal used for rounding.
vars	Vector including variables which should be displayed in summary. See the output stats.
...	Further arguments to be passed

**Details**

Let  $P_j(\alpha_l)$  the estimated item response function for the GDINA model and  $\hat{P}_j(\alpha_l)$  the item response model for the approximated model (DINA, DINO or ACDM). The unweighted distance `uwgtdist` as a measure of misfit is defined as

$$uwgtdist = \frac{1}{2^K} \sum_l (P_j(\alpha_l) - \hat{P}_j(\alpha_l))^2$$

The weighted distance `wgtdist` measures the discrepancy with respect to the probabilities  $w_l = P(\alpha_l)$  of estimated skill classes

$$wgtdist = \sum_l w_l (P_j(\alpha_l) - \hat{P}_j(\alpha_l))^2$$

**Value**

stats	Data frame with Wald statistic for every item, corresponding p values and a RMSEA fit statistic
-------	---

**References**

- de la Torre, J., & Lee, Y. S. (2013). Evaluating the Wald test for item-level comparison of saturated and reduced models in cognitive diagnosis. *Journal of Educational Measurement*, 50, 355-373.
- Ma, W., Iaconangelo, C., & de la Torre, J. (2016). Model similarity, model selection, and attribute classification. *Applied Psychological Measurement*, 40(3), 200-217.

**See Also**

See the `GDINA::modelcomp` function in the **GDINA** package for similar functionality.

**Examples**

```
## Not run:
#####
# EXAMPLE 1: Wald test for DINA simulated data sim.dina
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

# Model 1: estimate GDINA model
```

```

mod1 <- CDM::gdina( sim.dina, q.matrix=sim.qmatrix, rule="GDINA")
summary(mod1)

# perform Wald test
res1 <- CDM::gdina.wald( mod1 )
summary(res1)
# -> results show that all but one item fit according to the DINA rule

# select some output
summary(res1, vars=c("wgtdist", "p" )

## End(Not run)

```

gdm

*General Diagnostic Model***Description**

This function estimates the general diagnostic model (von Davier, 2008; Xu & von Davier, 2008) which handles multidimensional item response models with ordered discrete or continuous latent variables for polytomous item responses.

**Usage**

```

gdm( data, theta.k, irtmodel="2PL", group=NULL, weights=rep(1, nrow(data)),
      Qmatrix=NULL, thetaDes=NULL, skillspace="loglinear",
      b.constraint=NULL, a.constraint=NULL,
      mean.constraint=NULL, Sigma.constraint=NULL, delta.designmatrix=NULL,
      standardized.latent=FALSE, centered.latent=FALSE,
      centerintercepts=FALSE, centerslopes=FALSE,
      maxiter=1000, conv=1e-5, globconv=1e-5, msteps=4, convM=.0005,
      decrease.increments=FALSE, use.freqpatt=FALSE, progress=TRUE,
      PEM=FALSE, PEM_itermax=maxiter, ...)

## S3 method for class 'gdm'
summary(object, file=NULL, ...)

## S3 method for class 'gdm'
print(x, ...)

## S3 method for class 'gdm'
plot(x, perstype="EAP", group=1, barwidth=.1, histcol=1,
      cexcor=3, pchpers=16, cexpers=.7, ... )

```

**Arguments**

`data` An  $N \times I$  matrix of polytomous item responses with categories  $k = 0, 1, \dots, K$

theta.k	In the one-dimensional case it must be a vector. For multidimensional models it has to be a list of skill vectors if the theta grid differs between dimensions. If not, a vector input can be supplied. If an estimated skill space (skill space="est") should be estimated, a vector or a matrix theta.k will be used as initial values of the estimated $\theta$ grid.
irtmodel	The default 2PL corresponds to the model where item slopes on dimensions are equal for all item categories. If item-category slopes should be estimated, use 2PLcat. If no item slopes should be estimated then 1PL can be selected. Note that fixed item slopes can be specified in the Q-matrix (argument Qmatrix).
group	An optional vector of group identifiers for multiple group estimation. For plot.gdm it is an integer indicating which group should be used for plotting.
weights	An optional vector of sample weights
Qmatrix	An optional array of dimension $I \times D \times K$ which indicates pre-specified item loadings on dimensions. The default for category $k$ is the score $k$ , i.e. the scoring in the (generalized) partial credit model.
thetaDes	A design matrix for specifying nonlinear item response functions (see Example 1, Models 4 and 5)
skill space	The parametric assumption of the skill space. If skill space="normal" then a univariate or multivariate normal distribution is assumed. The default "loglinear" corresponds to log-linear smoothing of the skill space distribution (Xu & von Davier, 2008). If skill space="full", then all probabilities of the skill space are nonparametrically estimated. If skill space="est", then the $\theta$ distribution vectors will be estimated (see Details and Examples 4 and 5; Bartolucci, 2007).
b.constraint	In this optional matrix with $C_b$ rows and three columns, $C_b$ item intercepts $b_{ik}$ can be fixed. 1st column: item index, 2nd column: category index, 3rd column: fixed item thresholds
a.constraint	In this optional matrix with $C_a$ rows and four columns, $C_a$ item intercepts $a_{idk}$ can be fixed. 1st column: item index, 2nd column: dimension index, 3rd column: category index, 4th column: fixed item slopes
mean.constraint	A $C \times 3$ matrix for constraining $C$ means in the normal distribution assumption (skill space="normal"). 1st column: Dimension, 2nd column: Group, 3rd column: Value
Sigma.constraint	A $C \times 4$ matrix for constraining $C$ covariances in the normal distribution assumption (skill space="normal"). 1st column: Dimension 1, 2nd column: Dimension 2, 3rd column: Group, 4th column: Value
delta.designmatrix	The design matrix of $\delta$ parameters for the reduced skill space estimation (see Xu & von Davier, 2008)
standardized.latent	A logical indicating whether in a uni- or multidimensional model all latent variables of the first group should be normally distributed and standardized. The default is FALSE.

<code>centered.latent</code>	A logical indicating whether in a uni- or multidimensional model all latent variables of the first group should be normally distributed and do have zero means? The default is FALSE.
<code>centerintercepts</code>	A logical indicating whether intercepts should be centered to have a mean of 0 for all dimensions. This argument does not (yet) work properly for varying numbers of item categories.
<code>centerslopes</code>	A logical indicating whether item slopes should be centered to have a mean of 1 for all dimensions. This argument only works for <code>irtmodel="2PL"</code> . The default is FALSE.
<code>maxiter</code>	Maximum number of iterations
<code>conv</code>	Convergence criterion for item parameters and distribution parameters
<code>globconv</code>	Global deviance convergence criterion
<code>msteps</code>	Maximum number of M steps in estimating $b$ and $a$ item parameters. The default is to use 4 M steps.
<code>convM</code>	Convergence criterion in M step
<code>decrease.increments</code>	Should in the M step the increments of $a$ and $b$ parameters decrease during iterations? The default is FALSE. If there is an increase in deviance during estimation, setting <code>decrease.increments</code> to TRUE is recommended.
<code>use.freqpatt</code>	A logical indicating whether frequencies of unique item response patterns should be used. In case of large data set <code>use.freqpatt=TRUE</code> can speed calculations (depending on the problem). Note that in this case, not all person parameters are calculated as usual in the output.
<code>progress</code>	An optional logical indicating whether the function should print the progress of iteration in the estimation process.
<code>PEM</code>	Logical indicating whether the P-EM acceleration should be applied (Berlinet & Roland, 2012).
<code>PEM_itermax</code>	Number of iterations in which the P-EM method should be applied.
<code>object</code>	A required object of class <code>gdm</code>
<code>file</code>	Optional file name for a file in which summary should be sinked.
<code>x</code>	A required object of class <code>gdm</code>
<code>perstype</code>	Person parameter estimate type. Can be either "EAP", "MAP" or "MLE".
<code>barwidth</code>	Bar width in <code>plot.gdm</code>
<code>histcol</code>	Color of histogram bars in <code>plot.gdm</code>
<code>cexcor</code>	Font size for print of correlation in <code>plot.gdm</code>
<code>pchpers</code>	Point type for scatter plot of person parameters in <code>plot.gdm</code>
<code>cexpers</code>	Point size for scatter plot of person parameters in <code>plot.gdm</code>
<code>...</code>	Optional parameters to be passed to or from other methods will be ignored.

## Details

Case `irtmodel="1PL"`:

Equal item slopes of 1 are assumed in this model. Therefore, it corresponds to a generalized multi-dimensional Rasch model.

$$\text{logit}P(X_{nj} = k|\theta_n) = b_{j0} + \sum_d q_{jdk}\theta_{nd}$$

The Q-matrix entries  $q_{jdk}$  are pre-specified by the user.

Case `irtmodel="2PL"`:

For each item and each dimension, different item slopes  $a_{jd}$  are estimated:

$$\text{logit}P(X_{nj} = k|\theta_n) = b_{j0} + \sum_d a_{jd}q_{jdk}\theta_{nd}$$

Case `irtmodel="2PLcat"`:

For each item, each dimension and each category, different item slopes  $a_{jdk}$  are estimated:

$$\text{logit}P(X_{nj} = k|\theta_n) = b_{j0} + \sum_d a_{jdk}q_{jdk}\theta_{nd}$$

Note that this model can be generalized to include terms of any transformation  $t_h$  of the  $\theta_n$  vector (e.g. quadratic terms, step functions or interaction) such that the model can be formulated as

$$\text{logit}P(X_{nj} = k|\theta_n) = b_{j0} + \sum_h a_{jhk}q_{jhk}t_h(\theta_n)$$

In general, the number of functions  $t_1, \dots, t_H$  will be larger than the  $\theta$  dimension of  $D$ .

The estimation follows an EM algorithm as described in von Davier and Yamamoto (2004) and von Davier (2008).

In case of `skillspace="est"`, the  $\theta$  vectors (the grid of the theta distribution) are estimated (Bartolucci, 2007; Bacci, Bartolucci & Gnaldi, 2012). This model is called a multidimensional latent class item response model.

## Value

An object of class `gdm`. The list contains the following entries:

<code>item</code>	Data frame with item parameters
<code>person</code>	Data frame with person parameters: EAP denotes the mean of the individual posterior distribution, SE.EAP the corresponding standard error, MLE the maximum likelihood estimate at <code>theta.k</code> and MAP the mode of the posterior distribution
<code>EAP.rel</code>	Reliability of the EAP
<code>deviance</code>	Deviance
<code>ic</code>	Information criteria, number of estimated parameters
<code>b</code>	Item intercepts $b_{jk}$
<code>se.b</code>	Standard error of item intercepts $b_{jk}$

a	Item slopes $a_{jd}$ resp. $a_{jdk}$
se.a	Standard error of item slopes $a_{jd}$ resp. $a_{jdk}$
itemfit.rmsea	The RMSEA item fit index (see <a href="#">itemfit.rmsea</a> ). This entry comes as a list with total and group-wise item fit statistics.
mean.rmsea	Mean of RMSEA item fit indexes.
Qmatrix	Used Q-matrix
pi.k	Trait distribution
mean.trait	Means of trait distribution
sd.trait	Standard deviations of trait distribution
skewness.trait	Skewnesses of trait distribution
correlation.trait	List of correlation matrices of trait distribution corresponding to each group
pjk	Item response probabilities evaluated at grid theta.k
n.ik	An array of expected counts $n_{cikg}$ of ability class $c$ at item $i$ at category $k$ in group $g$
G	Number of groups
D	Number of dimension of $\theta$
I	Number of items
N	Number of persons
delta	Parameter estimates for skillspace representation
covdelta	Covariance matrix of parameter estimates for skillspace representation
data	Original data frame
group.stat	Group statistics (sample sizes, group labels)
p.xi.aj	Individual likelihood
posterior	Individual posterior distribution
skill.levels	Number of skill levels per dimension
K.item	Maximal category per item
theta.k	Used theta design or estimated theta trait distribution in case of <code>skillspace="est"</code>
thetaDes	Used theta design for item responses
se.theta.k	Estimated standard errors of theta.k if it is estimated
time	Info about computation time
skillspace	Used skillspace parametrization
iter	Number of iterations
converged	Logical indicating whether convergence was achieved.
object	Object of class <code>gdm</code>
x	Object of class <code>gdm</code>
perstype	Person parameter estimate type. Can be either "EAP", "MAP" or "MLE".
group	Group which should be used for <code>plot.gdm</code>

barwidth	Bar width in plot.gdm
histcol	Color of histogram bars in plot.gdm
cexcor	Font size for print of correlation in plot.gdm
pchpers	Point type for scatter plot of person parameters in plot.gdm
cexpers	Point size for scatter plot of person parameters in plot.gdm
...	Optional parameters to be passed to or from other methods will be ignored.

## References

- Bacci, S., Bartolucci, F., & Gnaldi, M. (2012). A class of multidimensional latent class IRT models for ordinal polytomous item responses. *arXiv preprint, arXiv:1201.4667*.
- Bartolucci, F. (2007). A class of multidimensional IRT models for testing unidimensionality and clustering items. *Psychometrika*, 72, 141-157.
- Berlinet, A. F., & Roland, C. (2012). Acceleration of the EM algorithm: P-EM versus epsilon algorithm. *Computational Statistics & Data Analysis*, 56(12), 4122-4137.
- von Davier, M. (2008). A general diagnostic model applied to language testing data. *British Journal of Mathematical and Statistical Psychology*, 61, 287-307.
- von Davier, M., & Yamamoto, K. (2004). Partially observed mixtures of IRT models: An extension of the generalized partial-credit model. *Applied Psychological Measurement*, 28, 389-406.
- Xu, X., & von Davier, M. (2008). *Fitting the structured general diagnostic model to NAEP data*. ETS Research Report ETS RR-08-27. Princeton, ETS.

## See Also

Cognitive diagnostic models for dichotomous data can be estimated with [din](#) (DINA or DINO model) or [gdina](#) (GDINA model, which contains many CDMs as special cases).

For assessment of model fit see [modelfit.cor.din](#) and [anova.gdm](#).

See [itemfit.sx2](#) for item fit statistics.

For the estimation of the multidimensional latent class item response model see the **MultiLCIRT** package and **sirt** package (function `sirt::rasch.mirtlc`).

## Examples

```
#####
# EXAMPLE 1: Fraction Dataset 1
#      Unidimensional Models for dichotomous data
#####

data(data.fraction1, package="CDM")
dat <- data.fraction1$data
theta.k <- seq( -6, 6, len=15 ) # discretized ability

###
# Model 1: Rasch model (normal distribution)
mod1 <- CDM::gdm( dat, irtmodel="1PL", theta.k=theta.k, skillspace="normal",
                 centered.latent=TRUE)
```

```

summary(mod1)
plot(mod1)

####
# Model 2: Rasch model (log-linear smoothing)
# set the item difficulty of the 8th item to zero
b.constraint <- matrix( c(8,1,0), 1, 3 )
mod2 <- CDM::gdm( dat, irtmodel="1PL", theta.k=theta.k,
                 skillspace="loglinear", b.constraint=b.constraint )
summary(mod2)

####
# Model 3: 2PL model
mod3 <- CDM::gdm( dat, irtmodel="2PL", theta.k=theta.k,
                 skillspace="normal", standardized.latent=TRUE )
summary(mod3)

## Not run:
####
# Model 4: include quadratic term in item response function
# using the argument decrease.increments=TRUE leads to a more
# stable estimate
thetaDes <- cbind( theta.k, theta.k^2 )
colnames(thetaDes) <- c( "F1", "F1q" )
mod4 <- CDM::gdm( dat, irtmodel="2PL", theta.k=theta.k,
                 thetaDes=thetaDes, skillspace="normal",
                 standardized.latent=TRUE, decrease.increments=TRUE)
summary(mod4)

####
# Model 5: step function for ICC
# two different probabilities  $\theta < 0$  and  $\theta > 0$ 
thetaDes <- matrix( 1*(theta.k>0), ncol=1 )
colnames(thetaDes) <- c( "Fgrm1" )
mod5 <- CDM::gdm( dat, irtmodel="2PL", theta.k=theta.k,
                 thetaDes=thetaDes, skillspace="normal" )
summary(mod5)

####
# Model 6: DINA model with din function
mod6 <- CDM::din( dat, q.matrix=matrix( 1, nrow=ncol(dat),ncol=1 ) )
summary(mod6)

####
# Model 7: Estimating a version of the DINA model with gdm
theta.k <- c(-.5,.5)
mod7 <- CDM::gdm( dat, irtmodel="2PL", theta.k=theta.k, skillspace="loglinear" )
summary(mod7)

#####
# EXAMPLE 2: Cultural Activities - data.Students
# Unidimensional Models for polytomous data
#####

```



```

data(data.Students, package="CDM")
dat <- data.Students

dat <- dat[, grep( "act", colnames(dat) ) ]
theta.k <- seq( -4, 4, len=11 ) # discretized ability

####
# Model 1: Partial Credit Model (PCM)
mod1 <- CDM::gdm( dat, irtmodel="1PL", theta.k=theta.k, skillspace="normal",
                 centered.latent=TRUE)
summary(mod1)
plot(mod1)

####
# Model 1b: PCM using frequency patterns
mod1b <- CDM::gdm( dat, irtmodel="1PL", theta.k=theta.k, skillspace="normal",
                  centered.latent=TRUE, use.freqpatt=TRUE)
summary(mod1b)

####
# Model 2: PCM with two groups
mod2 <- CDM::gdm( dat, irtmodel="1PL", theta.k=theta.k,
                 group=CDM::data.Students$urban + 1, skillspace="normal",
                 centered.latent=TRUE)
summary(mod2)

####
# Model 3: PCM with loglinear smoothing
b.constraint <- matrix( c(1,2,0), ncol=3 )
mod3 <- CDM::gdm( dat, irtmodel="1PL", theta.k=theta.k,
                 skillspace="loglinear", b.constraint=b.constraint )
summary(mod3)

####
# Model 4: Model with pre-specified item weights in Q-matrix
Qmatrix <- array( 1, dim=c(5,1,2) )
Qmatrix[,1,2] <- 2 # default is score 2 for category 2
# now change the scoring of category 2:
Qmatrix[c(2,4),1,1] <- .74
Qmatrix[c(2,4),1,2] <- 2.3
# for items 2 and 4 the score for category 1 is .74 and for category 2 it is 2.3
mod4 <- CDM::gdm( dat, irtmodel="1PL", theta.k=theta.k, Qmatrix=Qmatrix,
                 skillspace="normal", centered.latent=TRUE)
summary(mod4)

####
# Model 5: Generalized partial credit model
mod5 <- CDM::gdm( dat, irtmodel="2PL", theta.k=theta.k,
                 skillspace="normal", standardized.latent=TRUE )
summary(mod5)

####

```

```

# Model 6: Item-category slope estimation
mod6 <- CDM::gdm( dat, irtmodel="2PLcat", theta.k=theta.k, skillspace="normal",
                 standardized.latent=TRUE, decrease.increments=TRUE)
summary(mod6)

####
# Models 7: items with different number of categories
dat0 <- dat
dat0[ paste(dat0[,1])=="2, 1 ] <- 1 # 1st item has only two categories
dat0[ paste(dat0[,3])=="2, 3 ] <- 1 # 3rd item has only two categories

# Model 7a: PCM
mod7a <- CDM::gdm( dat0, irtmodel="1PL", theta.k=theta.k, centered.latent=TRUE )
summary(mod7a)

# Model 7b: Item category slopes
mod7b <- CDM::gdm( dat0, irtmodel="2PLcat", theta.k=theta.k,
                 standardized.latent=TRUE, decrease.increments=TRUE )
summary(mod7b)

#####
# EXAMPLE 3: Fraction Dataset 2
#      Multidimensional Models for dichotomous data
#####

data(data.fraction2, package="CDM")
dat <- data.fraction2$data
Qmatrix <- data.fraction2$q.matrix3

####
# Model 1: One-dimensional Rasch model
theta.k <- seq( -4, 4, len=11 ) # discretized ability
mod1 <- CDM::gdm( dat, irtmodel="1PL", theta.k=theta.k, centered.latent=TRUE)
summary(mod1)
plot(mod1)

####
# Model 2: One-dimensional 2PL model
mod2 <- CDM::gdm( dat, irtmodel="2PL", theta.k=theta.k, standardized.latent=TRUE)
summary(mod2)
plot(mod2)

####
# Model 3: 3-dimensional Rasch Model (normal distribution)
mod3 <- CDM::gdm( dat, irtmodel="1PL", theta.k=theta.k, Qmatrix=Qmatrix,
                 centered.latent=TRUE, globconv=5*1E-3, conv=1E-4 )
summary(mod3)

####
# Model 4: 3-dimensional Rasch model (loglinear smoothing)
# set some item parameters of items 4,1 and 2 to zero
b.constraint <- cbind( c(4,1,2), 1, 0 )
mod4 <- CDM::gdm( dat, irtmodel="1PL", theta.k=theta.k, Qmatrix=Qmatrix,

```

```

        b.constraint=b.constraint, skillspace="loglinear" )
summary(mod4)

####
# Model 5: define a different theta grid for each dimension
theta.k <- list( "Dim1"=seq( -5, 5, len=11 ),
                "Dim2"=seq(-5,5,len=8),
                "Dim3"=seq( -3,3,len=6) )
mod5 <- CDM::gdm( dat, irtmodel="1PL", theta.k=theta.k, Qmatrix=Qmatrix,
                 b.constraint=b.constraint, skillspace="loglinear")
summary(mod5)

####
# Model 6: multidimensional 2PL model (normal distribution)
theta.k <- seq( -5, 5, len=13 )
a.constraint <- cbind( c(8,1,3), 1:3, 1, 1 ) # fix some slopes to 1
mod6 <- CDM::gdm( dat, irtmodel="2PL", theta.k=theta.k, Qmatrix=Qmatrix,
                 centered.latent=TRUE, a.constraint=a.constraint, decrease.increments=TRUE,
                 skillspace="normal")
summary(mod6)

####
# Model 7: multidimensional 2PL model (loglinear distribution)
a.constraint <- cbind( c(8,1,3), 1:3, 1, 1 )
b.constraint <- cbind( c(8,1,3), 1, 0 )
mod7 <- CDM::gdm( dat, irtmodel="2PL", theta.k=theta.k, Qmatrix=Qmatrix,
                 b.constraint=b.constraint, a.constraint=a.constraint,
                 decrease.increments=FALSE, skillspace="loglinear")
summary(mod7)

#####
# EXAMPLE 4: Unidimensional latent class 1PL IRT model
#####

# simulate data
set.seed(754)
I <- 20      # number of items
N <- 2000    # number of persons
theta <- c( -2, 0, 1, 2 )
theta <- rep( theta, c(N/4,N/4, 3*N/8, N/8) )
b <- seq(-2,2,len=I)
library(sirt) # use function sim.raschtype from sirt package
dat <- sirt::sim.raschtype( theta=theta, b=b )

theta.k <- seq(-1, 1, len=4)      # initial vector of theta
# estimate model
mod1 <- CDM::gdm( dat, theta.k=theta.k, skillspace="est", irtmodel="1PL",
                 centerintercepts=TRUE, maxiter=200)
summary(mod1)
## Estimated Skill Distribution
##      F1      pi.k
## 1 -1.988 0.24813
## 2 -0.055 0.23313

```

```

## 3 0.940 0.40059
## 4 2.000 0.11816

#####
# EXAMPLE 5: Multidimensional latent class IRT model
#####

# We simulate a two-dimensional IRT model in which theta vectors
# are observed at a fixed discrete grid (see below).

# simulate data
set.seed(754)
I <- 13      # number of items
N <- 2400    # number of persons

# simulate Dimension 1 at 4 discrete theta points
theta <- c( -2, 0, 1, 2 )
theta <- rep( theta, c(N/4,N/4, 3*N/8, N/8) )
b <- seq(-2,2,len=I)
library(sirt) # use simulation function from sirt package
dat1 <- sirt::sim.raschtype( theta=theta, b=b )
# simulate Dimension 2 at 4 discrete theta points
theta <- c( -3, 0, 1.5, 2 )
theta <- rep( theta, c(N/4,N/4, 3*N/8, N/8) )
dat2 <- sirt::sim.raschtype( theta=theta, b=b )
colnames(dat2) <- gsub( "I", "U", colnames(dat2))
dat <- cbind( dat1, dat2 )

# define Q-matrix
Qmatrix <- matrix(0,2*I,2)
Qmatrix[ cbind( 1:(2*I), rep(1:2, each=I) ) ] <- 1

theta.k <- seq(-1, 1, len=4)      # initial matrix
theta.k <- cbind( theta.k, theta.k )
colnames(theta.k) <- c("Dim1", "Dim2")

# estimate model
mod2 <- CDM::gdm( dat, theta.k=theta.k, skillspace="est", irtmodel="1PL",
                  Qmatrix=Qmatrix, centerintercepts=TRUE)
summary(mod2)
## Estimated Skill Distribution
## theta.k.Dim1 theta.k.Dim2 pi.k
## 1 -2.022 -3.035 0.25010
## 2 0.016 0.053 0.24794
## 3 0.956 1.525 0.36401
## 4 1.958 1.919 0.13795

#####
# EXAMPLE 6: Large-scale dataset data.mg
#####

data(data.mg, package="CDM")
dat <- data.mg[, paste0("I", 1:11 ) ]

```

```

theta.k <- seq(-6,6,len=21)

****
# Model 1: Generalized partial credit model with multiple groups
mod1 <- CDM::gdm( dat, irtmodel="2PL", theta.k=theta.k, group=CDM::data.mg$group,
                 skillspace="normal", standardized.latent=TRUE)
summary(mod1)

## End(Not run)

```

---

ideal.response.pattern

*Ideal Response Pattern*

---

### Description

This function computes the ideal response pattern which is the latent item response  $\eta_{lj} = \prod_{k=1}^K \alpha_{lk}$  for a person with skill profile  $l$  at item  $j$ .

### Usage

```
ideal.response.pattern(q.matrix, skillspace=NULL, rule="DINA")
```

### Arguments

q.matrix	The Q-matrix
skillspace	An optional skill space matrix. If it is not provided, then all skill classes are used for creating an ideal response pattern.
rule	Chosen condensation rule for the CDM. Can be "DINA" or "DINO".

### Value

A list with following entries

idealresp	A matrix with ideal response patterns
skillspace	Used skill space

### Examples

```

#####
# EXAMPLE 1: Ideal response pattern sim.qmatrix
#####

data(sim.qmatrix, package="CDM")
q.matrix <- sim.qmatrix

#- ideal response pattern for DINA model
CDM::ideal.response.pattern(q.matrix)

```

```
#- ideal response pattern for DINO model
CDM::ideal.response.pattern( q.matrix, rule="DINO" )

# compute ideal responses for a reduced skill space
skillspace <- matrix( c( 0,1,0,
                       1,1,0 ), 2,3, byrow=TRUE )
CDM::ideal.response.pattern( q.matrix, skillspace=skillspace)
```

---

 IRT.anova

*Helper Function for Conducting Likelihood Ratio Tests*


---

### Description

This is a helper function for conducting likelihood ratio tests and can be generally used for objects for which the `logLik` method is defined.

### Usage

```
IRT.anova(object, ...)
```

### Arguments

<code>object</code>	Object for which the <code>logLik</code> method is defined.
<code>...</code>	A further object to be passed

### See Also

See also [IRT.compareModels](#) for model comparisons of several models.

See also as [anova.din](#).

---

 IRT.classify

*Individual Classification for Fitted Models*


---

### Description

Computes individual classifications based on a fitted model.

### Usage

```
IRT.classify(object, type="MLE")
```

**Arguments**

object	Fitted model for which methods <code>IRT.likelihood</code> and <code>IRT.posterior</code> are defined.
type	Type of classification: "MLE" (maximum likelihood estimate) or "MAP" (maximum of posterior distribution)

**Value**

List with entries

class_theta	Individual classification
class_index	Class index of individual classification
class_maxval	Maximum value corresponding to individual classification

**See Also**

See `IRT.factor.scores` for similar functionality.

**Examples**

```
## Not run:
#####
# EXAMPLE 1: Individual classification data.ecpe
#####

data(data.ecpe, package="CDM")
dat <- data.ecpe$dat[,-1]
Q <- data.ecpe$q.matrix

##* estimate GDINA model
mod <- CDM::gdina(dat, q.matrix=Q)
summary(mod)

##* classify individuals
cmod <- CDM::IRT.classify(mod)
str(cmod)

## End(Not run)
```

**Description**

Performs model comparisons based on information criteria and likelihood ratio test. This function allows all objects for which the `logLik(stats)` S3 method is defined. The output of `IRT.modelfit` can also be used as input for this function.

**Usage**

```
IRT.compareModels(object, ...)

## S3 method for class 'IRT.compareModels'
summary(object, extended=TRUE, ...)
```

**Arguments**

object	Object
extended	Optional logical indicating whether all or only a subset of fit statistics should be printed.
...	Further objects to be passed.

**Value**

A list with following entries

IC	Data frame with information criteria
LRtest	Data frame with all (useful) pairwise likelihood ratio tests

**See Also**

The function is based on [IRT.IC](#).

For comparing two models see [anova.din](#).

For computing absolute model fit see [IRT.modelfit](#).

**Examples**

```
## Not run:
#####
# EXAMPLE 1: Model comparison sim.dina dataset
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

dat <- sim.dina
q.matrix <- sim.qmatrix

#### Model 0: DINA model with equal guessing and slipping parameters
mod0 <- CDM::din( dat, q.matrix, guess.equal=TRUE, slip.equal=TRUE )
summary(mod0)

#### Model 1: DINA model
mod1 <- CDM::din( dat, q.matrix )
summary(mod1)

#### Model 2: DINO model
mod2 <- CDM::din( dat, q.matrix, rule="DINO")
```



```

summary(mod2)

#### Model 3: Additive GDINA model
mod3 <- CDM::gdina( dat, q.matrix, rule="ACDM")
summary(mod3)

#### Model 4: GDINA model
mod4 <- CDM::gdina( dat, q.matrix, rule="GDINA")
summary(mod4)

# model comparisons
res <- CDM::IRT.compareModels( mod0, mod1, mod2, mod3, mod4 )
res
## > res
## $IC
## Model loglike Deviance Npars Nobs AIC BIC AIC3 AICc CAIC
## 1 mod0 -2176.482 4352.963 9 400 4370.963 4406.886 4379.963 4371.425 4415.886
## 2 mod1 -2042.378 4084.756 25 400 4134.756 4234.543 4159.756 4138.232 4259.543
## 3 mod2 -2086.805 4173.610 25 400 4223.610 4323.396 4248.610 4227.086 4348.396
## 4 mod3 -2048.233 4096.466 32 400 4160.466 4288.193 4192.466 4166.221 4320.193
## 5 mod4 -2026.633 4053.266 41 400 4135.266 4298.917 4176.266 4144.887 4339.917
##
# -> The DINA model (mod1) performed best in terms of AIC.
## $LRtest
## Model1 Model2 Chi2 df p
## 1 mod0 mod1 268.20713 16 0.000000e+00
## 2 mod0 mod2 179.35362 16 0.000000e+00
## 3 mod0 mod3 256.49745 23 0.000000e+00
## 4 mod0 mod4 299.69671 32 0.000000e+00
## 5 mod1 mod3 -11.70967 7 1.000000e+00
## 6 mod1 mod4 31.48959 16 1.164415e-02
## 7 mod2 mod3 77.14383 7 5.262457e-14
## 8 mod2 mod4 120.34309 16 0.000000e+00
## 9 mod3 mod4 43.19926 9 1.981445e-06
##
# -> The GDINA model (mod4) was superior to the other models in terms
# of the likelihood ratio test.

# get an overview with summary
summary(res)
summary(res,extended=FALSE)

#####
# applying model comparison for objects of class IRT.modelfit

# compute model fit statistics
fmod0 <- CDM::IRT.modelfit(mod0)
fmod1 <- CDM::IRT.modelfit(mod1)
fmod4 <- CDM::IRT.modelfit(mod4)

# model comparison
res <- CDM::IRT.compareModels( fmod0, fmod1, fmod4 )
res

```

```

## $IC
##      Model  loglike Deviance Npars Nobs      AIC      BIC      AIC3
## mod0  mod0 -2176.482 4352.963    9 400 4370.963 4406.886 4379.963
## mod1  mod1 -2042.378 4084.756   25 400 4134.756 4234.543 4159.756
## mod4  mod4 -2026.633 4053.266   41 400 4135.266 4298.917 4176.266
##      AICc      CAIC      maxX2  p_maxX2      MADcor      SRMSR
## mod0 4371.425 4415.886 118.172707 0.0000000 0.09172287 0.10941300
## mod1 4138.232 4259.543   8.728248 0.1127943 0.03025354 0.03979948
## mod4 4144.887 4339.917   2.397241 1.0000000 0.02284029 0.02989669
##      X100.MADRESIDCOV      MADQ3      MADaQ3
## mod0      1.9749936 0.08840892 0.08353917
## mod1      0.6713952 0.06184332 0.05923058
## mod4      0.5148707 0.07477337 0.07145600
##
## $LRtest
##      Model1 Model2      Chi2 df      p
## 1  mod0  mod1 268.20713 16 0.0000000
## 2  mod0  mod4 299.69671 32 0.0000000
## 3  mod1  mod4  31.48959 16 0.01164415

## End(Not run)

```

---

IRT.data

*S3 Method for Extracting Used Item Response Dataset*


---

## Description

This S3 method extracts the used dataset with item responses.

## Usage

```

IRT.data(object, ...)

## S3 method for class 'din'
IRT.data(object, ...)

## S3 method for class 'gdina'
IRT.data(object, ...)

## S3 method for class 'gdm'
IRT.data(object, ...)

## S3 method for class 'mcdina'
IRT.data(object, ...)

## S3 method for class 'reglca'
IRT.data(object, ...)

## S3 method for class 'slca'
IRT.data(object, ...)

```

**Arguments**

object            Object of classes `din`, `gdina`, `mcdina`, `gdm`, `slca`, `reglca`.  
 ...              More arguments to be passed.

**Value**

A matrix (or data frame) with item responses and group identifier and weights vector as attributes.

**Examples**

```
## Not run:
#####
# EXAMPLE 1: Several models for sim.dina data
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

dat <- sim.dina
q.matrix <- sim.qmatrix

#--- Model 1: GDINA model
mod1 <- CDM::gdina( data=dat, q.matrix=q.matrix)
summary(mod1)
dmod1 <- CDM::IRT.data(mod1)
str(dmod1)

#--- Model 2: DINA model
mod2 <- CDM::din( data=dat, q.matrix=q.matrix)
summary(mod2)
dmod2 <- CDM::IRT.data(mod2)

#--- Model 3: Rasch model with gdm function
mod3 <- CDM::gdm( data=dat, irtmodel="1PL", theta.k=seq(-4,4,length=11),
                 centered.latent=TRUE )
summary(mod3)
dmod3 <- CDM::IRT.data(mod3)

#--- Model 4: Latent class model with two classes

dat <- sim.dina
I <- ncol(dat)

# define design matrices
TP <- 2        # two classes
# The idea is that latent classes refer to two different "dimensions".
# Items load on latent class indicators 1 and 2, see below.
Xdes <- array(0, dim=c(I,2,2,2*I) )
items <- colnames(dat)
dimnames(Xdes)[[4]] <- c(paste0( colnames(dat), "Class", 1),
                        paste0( colnames(dat), "Class", 2) )
# items, categories, classes, parameters
```

```

# probabilities for correct solution
for (ii in 1:I){
  Xdes[ ii, 2, 1, ii ] <- 1 # probabilities class 1
  Xdes[ ii, 2, 2, ii+I ] <- 1 # probabilities class 2
}
# estimate model
mod4 <- CDM::slca( dat, Xdes=Xdes)
summary(mod4)
dmod4 <- CDM::IRT.data(mod4)

## End(Not run)

```

---

IRT.expectedCounts      *S3 Method for Extracting Expected Counts*

---

### Description

This S3 method extracts expected counts from model output.

### Usage

```

IRT.expectedCounts(object, ...)

## S3 method for class 'din'
IRT.expectedCounts(object, ...)

## S3 method for class 'gdina'
IRT.expectedCounts(object, ...)

## S3 method for class 'gdm'
IRT.expectedCounts(object, ...)

## S3 method for class 'mcdina'
IRT.expectedCounts(object, ...)

## S3 method for class 'slca'
IRT.expectedCounts(object, ...)

## S3 method for class 'reglca'
IRT.expectedCounts(object, ...)

```

### Arguments

object	Object of classes <a href="#">din</a> , <a href="#">gdina</a> , <a href="#">mcdina</a> , <a href="#">gdm</a> or <a href="#">slca</a> .
...	More arguments to be passed.

### Value

An array with expected counts. The dimensions are items, categories, latent classes and groups.

**Examples**

```
## Not run:
#####
# EXAMPLE 1: Expected counts gdm function
#####

data(data.fraction1, package="CDM")
dat <- data.fraction1$data
theta.k <- seq( -6, 6, len=11 ) # discretized ability

#--- Model 1: Rasch model
mod1 <- CDM::gdm( dat, irtmodel="1PL", theta.k=theta.k, skillspace="normal",
                 centered.latent=TRUE )
emod1 <- CDM::IRT.expectedCounts(mod1)
str(emod1)

#####
# EXAMPLE 2: Expected counts gdina function
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

#--- Model 1: estimation of the GDINA model
mod1 <- CDM::gdina( data=sim.dina, q.matrix=sim.qmatrix)
summary(mod1)
emod1 <- CDM::IRT.expectedCounts(mod1)
str(emod1)

#--- Model 2: GDINA model with two groups
mod2 <- CDM::gdina( data=CDM::sim.dina, q.matrix=CDM::sim.qmatrix,
                  group=rep(1:2, each=200) )
summary(mod2)
emod2 <- CDM::IRT.expectedCounts( mod2 )
str(emod2)

## End(Not run)
```

---

IRT.factor.scores

*S3 Methods for Extracting Factor Scores (Person Classifications)*


---

**Description**

This S3 method extracts factor scores or skill classifications.

**Usage**

```
IRT.factor.scores(object, ...)
```

```
## S3 method for class 'din'
IRT.factor.scores(object, type="MLE", ...)

## S3 method for class 'gdina'
IRT.factor.scores(object, type="MLE", ...)

## S3 method for class 'mcdina'
IRT.factor.scores(object, type="MLE", ...)

## S3 method for class 'gdm'
IRT.factor.scores(object, type="EAP", ...)

## S3 method for class 'slca'
IRT.factor.scores(object, type="MLE", ...)
```

### Arguments

object	Object of classes <a href="#">din</a> , <a href="#">gdina</a> , <a href="#">mcdina</a> , <a href="#">gdm</a> or <a href="#">slca</a> .
type	Type of estimated factor score. This can be "MLE", "MAP" or "EAP". The type EAP cannot be used for objects of class <a href="#">slca</a> .
...	More arguments to be passed.

### Value

A matrix or a vector with classified scores.

### See Also

For extracting the individual likelihood or the individual posterior see [IRT.likelihood](#) or [IRT.posterior](#).

### Examples

```
#####
# EXAMPLE 1: Extracting factor scores in the DINA model
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

# estimate DINA model
mod1 <- CDM::din( sim.dina, q.matrix=sim.qmatrix)
summary(mod1)
# MLE
fsc1a <- CDM::IRT.factor.scores(mod1)
# MAP
fsc1b <- CDM::IRT.factor.scores(mod1, type="MAP")
# EAP
fsc1c <- CDM::IRT.factor.scores(mod1, type="EAP")
# compare classification for skill 1
stats::xtabs( ~ fsc1a[,1] + fsc1b[,1] )
graphics::boxplot( fsc1c[,1] ~ fsc1a[,1] )
```

---

IRT.frequencies	<i>S3 Method for Computing Observed and Expected Frequencies of Univariate and Bivariate Marginals</i>
-----------------	--

---

**Description**

This S3 method computes observed and expected frequencies for univariate and bivariate distributions.

**Usage**

```
IRT.frequencies(object, ...)

IRT_frequencies_default(data, post, probs, weights=NULL)

IRT_frequencies_wrapper(object, ...)

## S3 method for class 'din'
IRT.frequencies(object, ...)

## S3 method for class 'gdina'
IRT.frequencies(object, ...)

## S3 method for class 'mcdina'
IRT.frequencies(object, ...)

## S3 method for class 'gdm'
IRT.frequencies(object, ...)

## S3 method for class 'slca'
IRT.frequencies(object, ...)
```

**Arguments**

object	Object of classes <a href="#">din</a> , <a href="#">gdina</a> , <a href="#">mcdina</a> , <a href="#">gdm</a> or <a href="#">slca</a> .
...	More arguments to be passed.
data	Item response data as extracted by <a href="#">IRT.data</a>
post	Individual posterior distribution as extracted by <a href="#">IRT.posterior</a>
probs	Individual posterior distribution as extracted by <a href="#">IRT.irfprob</a>
weights	Optional vector of weights as included as the attribute <code>weights</code> in <a href="#">IRT.data</a>

**Value**

List with following entries

uni_obs	Univariate observed distribution
---------	----------------------------------

uni_exp	Univariate expected distribution
M_obs	Univariate observed means
M_exp	Univariate expected means
SD_obs	Univariate observed standard deviations
SD_exp	Univariate expected standard deviations
biv_obs	Bivariate observed frequencies
biv_exp	Bivariate expected frequencies
biv_N	Bivariate sample size
cov_obs	Observed covariances
cov_cor	Expected covariances
cor_obs	Observed correlations
cor_exp	Expected correlations
chisq	Chi square statistic of local independence

### Examples

```
## Not run:
#####
# EXAMPLE 1: Usage IRT.frequencies
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

# estimate GDINA model
mod1 <- CDM::gdina( data=sim.dina, q.matrix=sim.qmatrix)
summary(mod1)

# direct usage of IRT.frequencies
fres1 <- CDM::IRT.frequencies(mod1)

# use of the default function with input data
data <- CDM::IRT.data(object)
post <- CDM::IRT.posterior(object)
probs <- CDM::IRT.irfprob(object)
fres2 <- CDM::IRT_frequencies_default(data=data, post=post, probs=probs)

## End(Not run)
```

---

 IRT.IC

*Information Criteria*


---

### Description

Computes several information criteria for objects which do have the `logLik (stats)` S3 method (e.g. `din`, `gdina`, `gdm`, ...).



**Usage**

```
IRT.IC(object)
```

**Arguments**

object                    Objects which do have the `logLik (stats)` S3 method.

**Value**

A vector with deviance and several information criteria.

**See Also**

See also `anova.din` for model comparisons. A general method is defined in `IRT.compareModels`.

**Examples**

```
#####
# EXAMPLE 1: DINA example information criteria
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

###* Model 1: DINA model
mod1 <- CDM::din( sim.dina, q.matrix=sim.qmatrix )
summary(mod1)
IRT.IC(mod1)
```

---

 IRT.irfprob

---

*S3 Methods for Extracting Item Response Functions*


---

**Description**

This S3 method extracts item response functions evaluated at a grid of abilities (skills). Item response functions can be plotted using the `IRT.irfprobPlot` function.

**Usage**

```
IRT.irfprob(object, ...)

## S3 method for class 'din'
IRT.irfprob(object, ...)

## S3 method for class 'gdina'
IRT.irfprob(object, ...)

## S3 method for class 'gdm'
```

```
IRT.irfprob(object, ...)

## S3 method for class 'mcdina'
IRT.irfprob(object, ...)

## S3 method for class 'reglca'
IRT.irfprob(object, ...)

## S3 method for class 'slca'
IRT.irfprob(object, ...)
```

### Arguments

object	Object of classes <a href="#">din</a> , <a href="#">gdina</a> , <a href="#">mcdina</a> , <a href="#">gdm</a> , <a href="#">slca</a> , <a href="#">reglca</a> .
...	More arguments to be passed.

### Value

An array with item response probabilities (items  $\times$  categories  $\times$  skill classes [ $\times$  group]) and attributes

theta	Uni- or multidimensional skill space (theta grid in item response models).
prob.theta	Probability distribution of theta
skillspace	Design matrix and estimated parameters for skill space distribution (only for <code>IRT.posterior.slca</code> )
G	Number of groups

### See Also

Plot functions for item response curves: [IRT.irfprobPlot](#).

For extracting the individual likelihood or posterior see [IRT.likelihood](#) or [IRT.posterior](#).

### Examples

```
## Not run:
#####
# EXAMPLE 1: Extracting item response functions mcdina model
#####

data(data.cdm02, package="CDM")

dat <- data.cdm02$data
q.matrix <- data.cdm02$q.matrix

#-- estimate model
mod1 <- CDM::mcdina( dat, q.matrix=q.matrix)
#-- extract item response functions
prmod1 <- CDM::IRT.irfprob(mod1)
str(prmod1)
```

```
## End(Not run)
```

---

```
IRT.irfprobPlot      Plot Item Response Functions
```

---

## Description

This function plots item response functions for fitted item response models for which the `IRT.irfprob` method is defined.

## Usage

```
IRT.irfprobPlot( object, items=NULL, min.theta=-4, max.theta=4, cumul=FALSE,
  smooth=TRUE, ask=TRUE, n.theta=40, package="lattice",... )
```

## Arguments

<code>object</code>	Fitted item response model for which the <code>IRT.irfprob</code> method is defined
<code>items</code>	Vector of indices of selected items.
<code>min.theta</code>	Minimum theta to be displayed.
<code>max.theta</code>	Maximum theta to be displayed.
<code>cumul</code>	Optional logical indicating whether cumulated item response functions $P(X \geq k \theta)$ should be displayed.
<code>smooth</code>	Optional logical indicating whether item response functions should be smoothed for plotting.
<code>ask</code>	Logical for asking for a new plot.
<code>n.theta</code>	Number of theta points if <code>smooth=TRUE</code> is chosen.
<code>package</code>	String indicating which package should be used for plotting the item response curves. Options are "lattice" or "graphics".
<code>...</code>	More arguments to be passed for the plot in <b>lattice</b> .

## Examples

```
## Not run:
#####
# EXAMPLE 1: Plot item response functions from a unidimensional model
#####

data(data.Students, package="CDM")

dat <- data.Students
resp <- dat[, paste0("sc",1:4) ]
resp[ paste(resp[,1])==3,1] <- 2
psych::describe(resp)

#--- Model 1: PCM in CDM::gdm
```

```

theta.k <- seq( -5, 5, len=21 )
mod1 <- CDM::gdm( dat=resp, irtmodel="1PL", theta.k=theta.k, skillspace="normal",
                centered.latent=TRUE)
summary(mod1)

# plot
IRT.irfprobPlot( mod1 )
# plot in graphics package (which comes with R base version)
IRT.irfprobPlot( mod1, package="graphics")
# plot first and third item and do not smooth discretized item response
# functions in IRT.irfprob
IRT.irfprobPlot( mod1, items=c(1,3), smooth=FALSE )
# cumulated IRF
IRT.irfprobPlot( mod1, cumul=TRUE )

#####
# EXAMPLE 2: Fitted multidimensional model with gdm
#####

dat <- CDM::data.fraction2$data
Qmatrix <- CDM::data.fraction2$q.matrix3

# Model 1: 3-dimensional Rasch Model (normal distribution)
theta.k <- seq( -4, 4, len=11 ) # discretized ability
mod1 <- CDM::gdm( dat, irtmodel="1PL", theta.k=theta.k, Qmatrix=Qmatrix,
                centered.latent=TRUE, maxiter=10 )
summary(mod1)

# unsmoothed curves
IRT.irfprobPlot(mod1, smooth=FALSE)
# smoothed curves
IRT.irfprobPlot(mod1)

## End(Not run)

```

---

IRT.itemfit

*S3 Methods for Computing Item Fit*


---

## Description

This S3 method computes some selected item fit statistic.

## Usage

```

IRT.itemfit(object, ...)

## S3 method for class 'din'
IRT.itemfit(object, method="RMSEA", ...)

## S3 method for class 'gdina'

```

```
IRT.itemfit(object, method="RMSEA", ...)

## S3 method for class 'gdm'
IRT.itemfit(object, method="RMSEA", ...)

## S3 method for class 'reglca'
IRT.itemfit(object, method="RMSEA", ...)

## S3 method for class 'slca'
IRT.itemfit(object, method="RMSEA", ...)
```

### Arguments

object	Object of classes <a href="#">din</a> , <a href="#">gdina</a> , <a href="#">gdm</a> , <a href="#">slca</a> , <a href="#">reglca</a> .
method	Method for computing item fit statistic. Until now, only method="RMSEA" (see <a href="#">itemfit.rmsea</a> ) can be used.
...	More arguments to be passed.

### Value

Vector or data frame with item fit statistics.

### See Also

For extracting the individual likelihood or posterior see [IRT.likelihood](#) or [IRT.posterior](#).

### Examples

```
## Not run:
#####
# EXAMPLE 1: DINA model item fit
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

# estimate model
mod1 <- CDM::din( sim.dina, q.matrix=sim.qmatrix)
# compute item fit
IRT.itemfit( mod1 )

## End(Not run)
```

---

 IRT.jackknife

*Jackknifing an Item Response Model*


---

### Description

This function performs a Jackknife procedure for estimating standard errors for an item response model. The replication design must be defined by [IRT.repDesign](#). Model fit is also assessed via Jackknife.

Statistical inference for derived parameters is performed by `IRT.derivedParameters` with a fitted object of class `IRT.jackknife` and a list with defining formulas.

### Usage

```
IRT.jackknife(object,repDesign, ... )

IRT.derivedParameters(jkobject, derived.parameters )

## S3 method for class 'gdina'
IRT.jackknife(object, repDesign, ...)

## S3 method for class 'IRT.jackknife'
coef(object, bias.corr=FALSE, ...)

## S3 method for class 'IRT.jackknife'
vcov(object, ...)
```

### Arguments

<code>object</code>	Objects for which S3 method <code>IRT.jackknife</code> is defined.
<code>repDesign</code>	Replication design generated by <a href="#">IRT.repDesign</a> .
<code>jkobject</code>	Object of class <code>IRT.jackknife</code> .
<code>derived.parameters</code>	List with defined derived parameters (see Example 2, Model 2).
<code>bias.corr</code>	Optional logical indicating whether a bias correction should be employed.
<code>...</code>	Further arguments to be passed.

### Value

List with following entries

<code>jpartable</code>	Parameter table with Jackknife estimates
<code>parsM</code>	Matrix with replicated statistics
<code>vcov</code>	Variance covariance matrix of parameters

## Examples

```

## Not run:
library(BIFIEsurvey)

#####
# EXAMPLE 1: Multiple group DINA model with TIMSS data | Cluster sample
#####

data(data.timss11.G4.AUT.part, package="CDM")

dat <- data.timss11.G4.AUT.part$data
q.matrix <- data.timss11.G4.AUT.part$q.matrix2
# extract items
items <- paste(q.matrix$item)

# generate replicate design
rdes <- CDM::IRT.repDesign( data=dat, wgt="TOTWGT", jktype="JK_TIMSS",
                           jkzone="JKCZONE", jkrep="JKCREP" )

#--- Model 1: fit multiple group GDINA model
mod1 <- CDM::gdina( dat[,items], q.matrix=q.matrix[,-1],
                   weights=dat$TOTWGT, group=dat$female +1 )
# jackknife Model 1
jmod1 <- CDM::IRT.jackknife( object=mod1, repDesign=rdes )
summary(jmod1)
coef(jmod1)
vcov(jmod1)

#####
# EXAMPLE 2: DINA model | Simple random sampling
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")
dat <- sim.dina
q.matrix <- sim.qmatrix

# generate replicate design with 50 jackknife zones (50 random groups)
rdes <- CDM::IRT.repDesign( data=dat, jktype="JK_RANDOM", ngr=50 )

#--- Model 1: DINA model
mod1 <- CDM::gdina( dat, q.matrix=q.matrix, rule="DINA")
summary(mod1)
# jackknife DINA model
jmod1 <- CDM::IRT.jackknife( object=mod1, repDesign=rdes )
summary(jmod1)

#--- Model 2: DINO model
mod2 <- CDM::gdina( dat, q.matrix=q.matrix, rule="DINO")
summary(mod2)
# jackknife DINA model
jmod2 <- CDM::IRT.jackknife( object=mod2, repDesign=rdes )

```

```

summary(jmod2)
IRT.compareModels( mod1, mod2 )

# statistical inference for derived parameters
derived.parameters <- list( "skill1"=~ 0 + I(prob_skillV1_lev1_group1),
  "skilldiff12"=~ 0 + I( prob_skillV2_lev1_group1 - prob_skillV1_lev1_group1 ),
  "skilldiff13"=~ 0 + I( prob_skillV3_lev1_group1 - prob_skillV1_lev1_group1 )
)
jmod2a <- CDM::IRT.derivedParameters( jmod2, derived.parameters=derived.parameters )
summary(jmod2a)
coef(jmod2a)

## End(Not run)

```

---

IRT.likelihood	<i>S3 Methods for Extracting of the Individual Likelihood and the Individual Posterior</i>
----------------	--

---

## Description

Functions for extracting the individual likelihood and individual posterior distribution.

## Usage

```

IRT.likelihood(object, ...)

IRT.posterior(object, ...)

## S3 method for class 'din'
IRT.likelihood(object, ...)
## S3 method for class 'din'
IRT.posterior(object, ...)

## S3 method for class 'gdina'
IRT.likelihood(object, ...)
## S3 method for class 'gdina'
IRT.posterior(object, ...)

## S3 method for class 'gdm'
IRT.likelihood(object, ...)
## S3 method for class 'gdm'
IRT.posterior(object, ...)

## S3 method for class 'mcdina'
IRT.likelihood(object, ...)
## S3 method for class 'mcdina'
IRT.posterior(object, ...)

```



```
## S3 method for class 'reglca'
IRT.likelihood(object, ...)
## S3 method for class 'reglca'
IRT.posterior(object, ...)

## S3 method for class 'slca'
IRT.likelihood(object, ...)
## S3 method for class 'slca'
IRT.posterior(object, ...)
```

### Arguments

object	Object of classes <a href="#">din</a> , <a href="#">gdina</a> , <a href="#">mcdina</a> , <a href="#">gdm</a> , <a href="#">slca</a> , <a href="#">reglca</a> .
...	More arguments to be passed.

### Value

For both functions `IRT.likelihood` and `IRT.posterior`, it is a matrix with attributes

theta	Uni- or multidimensional skill space (theta grid in item response models).
prob.theta	Probability distribution of theta
skillspace	Design matrix and estimated parameters for skill space distribution (only for <code>IRT.posterior.slca</code> )
G	Number of groups

### See Also

[GDINA::indlogLik](#), [GDINA::indlogPost](#)

### Examples

```
#####
# EXAMPLE 1: Extracting likelihood and posterior from a DINA model
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

###* estimate model
mod1 <- CDM::din( sim.dina, q.matrix=sim.qmatrix, rule="DINA")
###* extract likelihood
likemod1 <- CDM::IRT.likelihood(mod1)
str(likemod1)
# extract theta
attr(likemod1, "theta" )
###* extract posterior
pomod1 <- CDM::IRT.posterior( mod1 )
str(pomod1)
```

---

 IRT.marginal\_posterior

*S3 Method for Computation of Marginal Posterior Distribution*


---

### Description

Computes marginal posterior distributions for fitted models in the **CDM** package.

### Usage

```
IRT.marginal_posterior(object, dim, remove_zeroprobs=TRUE, ...)

## S3 method for class 'din'
IRT.marginal_posterior(object, dim, remove_zeroprobs=TRUE, ...)
## S3 method for class 'gdina'
IRT.marginal_posterior(object, dim, remove_zeroprobs=TRUE, ...)
## S3 method for class 'mcdina'
IRT.marginal_posterior(object, dim, remove_zeroprobs=TRUE, ...)
```

### Arguments

object	Object of class <a href="#">din</a> , <a href="#">gdina</a> , <a href="#">mcdina</a>
dim	Numeric or character vector indicating dimensions of posterior distribution which should be marginalized
remove_zeroprobs	Logical indicating whether classes with zero probabilities should be removed
...	Further arguments to be passed

### Value

List with entries	
marg_post	Marginal posterior distribution
map	MAP estimate (individual classification)
theta	Skill classes

### See Also

[IRT.posterior](#)

**Examples**

```

## Not run:
#####
# EXAMPLE 1: Dataset with three hierarchical skills
#####

# simulated data with hierarchical skills:
# skill A with 4 levels, skill B with 2 levels and skill C with 3 levels

data(data.cdm10, package="CDM")
dat <- data.cdm10$data
Q <- data.cdm10$q.matrix
print(Q)

# define hierarchical skill structure
B <- "A1 > A2 > A3
      C1 > C2"
skill_space <- CDM::skillspace.hierarchy(B=B, skill.names=colnames(Q))
zeroprob.skillclasses <- skill_space$zeroprob.skillclasses

# estimate DINA model
mod1 <- CDM::gdina( dat, q.matrix=Q, zeroprob.skillclasses=zeroprob.skillclasses, rule="DINA")
summary(mod1)

# classification for skill A
res <- CDM::IRT.marginal_posterior(object=mod1, dim=c("A1","A2","A3") )
table(res$map)

# classification for skill B
res <- CDM::IRT.marginal_posterior(object=mod1, dim=c("B") )
table(res$map)

# classification for skill C
res <- CDM::IRT.marginal_posterior(object=mod1, dim=c("C1","C2") )
table(res$map)

## End(Not run)

```

**Description**

This S3 method assesses global (absolute) model fit using the methods described in [modelfit.cor.din](#).

**Usage**

```
IRT.modelfit(object, ...)
```

```
## S3 method for class 'din'
IRT.modelfit(object, ...)
## S3 method for class 'gdina'
IRT.modelfit(object, ...)

## S3 method for class 'IRT.modelfit.din'
summary(object, ...)
## S3 method for class 'IRT.modelfit.gdina'
summary(object, ...)
```

### Arguments

```
object      Object of classes din or gdina.
...         More arguments to be passed.
```

### Value

See output of [modelfit.cor.din](#).

### See Also

For extracting the individual likelihood or posterior see [IRT.likelihood](#) or [IRT.posterior](#).

The model fit of objects of class [gdm](#) can be obtained by using the `TAM::tam.modelfit.IRT` function in the **TAM** package.

### Examples

```
## Not run:
#####
# EXAMPLE 1: Absolute model fit
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

**** Model 1: DINA model for DINA simulated data
mod1 <- CDM::din( sim.dina, q.matrix=sim.qmatrix, rule="DINA" )
fmod1 <- CDM::IRT.modelfit( mod1 )
summary(fmod1)
## Test of Global Model Fit
##      type value    p
## 1  max(X2) 8.728 0.113
## 2  abs(fcor) 0.143 0.080
##
## Fit Statistics
##           est
## MADcor      0.030
## SRMSR        0.040
## 100*MADRESIDCOV 0.671
## MADQ3        0.062
## MADaQ3       0.059
```

```
### Model 2: GDINA model
mod2 <- CDM::gdina( sim.dina, q.matrix=sim.qmatrix, rule="GDINA" )
fmod2 <- CDM::IRT.modelfit( mod2 )
summary(fmod2)
## Test of Global Model Fit
##      type value p
## 1  max(X2) 2.397 1
## 2  abs(fcor) 0.078 1
##
## Fit Statistics
##              est
## MADcor        0.023
## SRMSR         0.030
## 100*MADRESIDCOV 0.515
## MADQ3         0.075
## MADaQ3        0.071

## End(Not run)
```

---

IRT.parameterTable      *S3 Method for Extracting a Parameter Table*

---

### Description

S3 method which extracts a parameter table.

### Usage

```
IRT.parameterTable(object, ...)
```

### Arguments

object	Object of model classes
...	More arguments to be passed.

### Value

A parameter table

IRT.repDesign

*Generation of a Replicate Design for IRT.jackknife***Description**

This function generates a Jackknife replicate design which is necessary to use the IRT.jackknife function. The function is a wrapper to BIFIE.data.jack in the **BIFIEsurvey** package.

**Usage**

```
IRT.repDesign(data, wgt=NULL, jktype="JK_TIMSS", jkzone=NULL, jkrep=NULL,
              jkfac=NULL, fayfac=1, wgtrep="W_FSTR", ngr=100, Nboot=200, seed=.Random.seed)
```

**Arguments**

data	Dataset which must contain weights and item responses
wgt	Vector with sample weights
jktype	Type of jackknife procedure for creating the BIFIE.data object. jktype="JK_TIMSS" refers to TIMSS/PIRLS datasets. The type "JK_GROUP" creates jackknife weights based on a user defined grouping, the type "JK_RANDOM" creates random groups. The number of random groups can be defined in ngr. The argument type="RW_PISA" extracts the replicated design with balanced repeated replicate weights from PISA datasets into objects of class IRT.repDesign. Bootstrap samples can be obtained by type="BOOT".
jkzone	Variable name for jackknife zones. If jktype="JK_TIMSS", then jkzone="JKZONE". However, this default can be overwritten.
jkrep	Variable name containing Jackknife replicates
jkfac	Factor for multiplying jackknife replicate weights. If jktype="JK_TIMSS", then jkfac=2.
fayfac	Fay factor. For Jackknife, the default is 1. For a Bootstrap with $R$ samples with replacement, the Fay factor is $1/R$ .
wgtrep	Already available replicate design
ngr	Number of groups
Nboot	Number of bootstrap samples
seed	Random seed

**Value**

A list with following entries

wgt	Vector with weights
wgtrep	Matrix containing the replicate design
fayfac	Fay factor needed for Jackknife calculations

**See Also**

See [IRT.jackknife](#) for further examples.

See the `BIFIE.data.jack` function in the **BIFIEsurvey** package.

**Examples**

```
## Not run:
# load the BIFIEsurvey package
library(BIFIEsurvey)

#####
# EXAMPLE 1: Design with Jackknife replicate weights in TIMSS
#####

data(data.timss11.G4.AUT, package="CDM")
dat <- CDM::data.timss11.G4.AUT$data
# generate design
rdes <- CDM::IRT.repDesign( data=dat, wgt="TOTWGT", jktype="JK_TIMSS",
                           jkzone="JKCZONE", jkrep="JKCREP" )
str(rdes)

#####
# EXAMPLE 2: Bootstrap resampling
#####

data(sim.qmatrix, package="CDM")
q.matrix <- CDM::sim.qmatrix

# simulate data according to the DINA model
dat <- CDM::sim.din(N=2000, q.matrix=q.matrix )$dat

# bootstrap with 300 random samples
rdes <- CDM::IRT.repDesign( data=dat, jktype="BOOT", Nboot=300 )

## End(Not run)
```

---

 IRT.RMSD

*Root Mean Square Deviation (RMSD) Item Fit Statistic*


---

**Description**

Computed the item fit statistics root mean square deviation (RMSD), mean absolute deviation (MAD) and mean deviation (MD). See Oliveri and von Davier (2011) for details.

The RMSD statistics was denoted as the RMSEA statistic in older publications, see [itemfit.rmsea](#).

If multiple groups are defined in the model object, a weighted item fit statistic (WRMSD; Yamamoto, Khorramdel, & von Davier, 2013; von Davier, Weeks, Chen, Allen & van der Velden, 2013) is additionally computed.

**Usage**

```
IRT.RMSD(object)

## S3 method for class 'IRT.RMSD'
summary(object, file=NULL, digits=3, ...)

## core computation function
IRT_RMSD_calc_rmsd( n.ik, pi.k, probs, eps=1E-30 )
```

**Arguments**

object	Object for which the methods <code>IRT.expectedCounts</code> and <code>IRT.irfprob</code> can be applied.
n.ik	Expected counts
pi.k	Probabilities trait distribution
probs	Item response probabilities
eps	Numerical constant avoiding division by zero
digits	Number of digits used for rounding
file	Optional file name for a file in which summary should be sinked.
...	Optional parameters to be passed.

**Details**

The RMSD and MD statistics are in operational use in PISA studies since PISA 2015. These fit statistics can also be used for investigating uniform and nonuniform differential item functioning.

**Value**

List with entries	
RMSD	Item-wise and group-wise RMSD statistic
RMSD_bc	Item-wise and group-wise RMSD statistic with analytical bias correction
MAD	Item-wise and group-wise MAD statistic
MD	Item-wise and group-wise MD statistic
chisquare_stat	Item-wise and group-wise $\chi^2$ statistic
...	Further values

**References**

Oliveri, M. E., & von Davier, M. (2011). Investigation of model fit and score scale comparability in international assessments. *Psychological Test and Assessment Modeling*, *53*, 315-333.

von Davier, M., Weeks, J., Chen, H., Allen, J., & van der Velden, R. (2013). Creating simple and complex derived variables and validation of background questionnaire data. In OECD (Eds.). *Technical Report of the Survey of Adults Skills (PIAAC)* (Ch. 20). Paris: OECD.

Yamamoto, K., Khorramdel, L., & von Davier, M. (2013). Scaling PIAAC cognitive data. In OECD (Eds.). *Technical Report of the Survey of Adults Skills (PIAAC)* (Ch. 17). Paris: OECD.



**See Also**

[itemfit.rmsea](#)

**Examples**

```
## Not run:
#####
# EXAMPLE 1: data.read | 1PL model in TAM
#####

data(data.read, package="sirt")
dat <- data.read

*** Model 1: 1PL model
mod1 <- TAM::tam.mml( resp=dat )
summary(mod1)

# item fit statistics
imod1 <- CDM::IRT.RMSD(mod1)
summary(imod1)

#####
# EXAMPLE 2: data.math| RMSD and MD statistic for assessing DIF
#####

data(data.math, package="sirt")
dat <- data.math$data
items <- grep("M[A-Z]", colnames(dat), value=TRUE )

#-- fit multiple group Rasch model
mod <- TAM::tam.mml( dat[,items], group=dat$female )
summary(mod)

#-- fit statistics
rmod <- CDM::IRT.RMSD(mod)
summary(rmod)

#####
# EXAMPLE 3: RMSD statistic DINA model
#####

data(sim.dina)
data(sim.qmatrix)
dat <- sim.dina
Q <- sim.qmatrix

#-- fit DINA model
mod1 <- CDM::gdina( dat, q.matrix=Q, rule="DINA" )
summary(mod1)

#-- compute RMSD fit statistic
rmod1 <- CDM::IRT.RMSD(mod1)
```

```
summary(rmod1)
## End(Not run)
```

---

itemfit.rmsea	<i>RMSEA Item Fit</i>
---------------	-----------------------

---

### Description

This function estimates a chi squared based measure of item fit in cognitive diagnosis models similar to the RMSEA itemfit implemented in mdltm (von Davier, 2005; cited in Kunina-Habenicht, Rupp & Wilhelm, 2009).

The RMSEA statistic is also called as the RMSD statistic, see [IRT.RMSD](#).

### Usage

```
itemfit.rmsea(n.ik, pi.k, probs, itemnames=NULL)
```

### Arguments

n.ik	An array of four dimensions: Classes x items x categories x groups
pi.k	An array of two dimensions: Classes x groups
probs	An array of three dimensions: Classes x items x categories
itemnames	An optional vector of item names. Default is NULL.

### Details

For item  $j$ , the RMSEA itemfit in this function is calculated as follows:

$$RMSEA_j = \sqrt{\sum_k \sum_c \pi(\theta_c) \left( P_j(\theta_c) - \frac{n_{jkc}}{N_{jc}} \right)^2}$$

where  $c$  denotes the class of the skill vector  $\theta$ ,  $k$  is the item category,  $\pi(\theta_c)$  is the estimated class probability of  $\theta_c$ ,  $P_j$  is the estimated item response function,  $n_{jkc}$  is the expected number of students with skill  $\theta_c$  on item  $j$  in category  $k$  and  $N_{jc}$  is the expected number of students with skill  $\theta_c$  on item  $j$ .

### Value

A list with two entries:

rmsea	Vector of RMSEA item statistics
rmsea.groups	Matrix of group-wise RMSEA item statistics

## References

- Kunina-Habenicht, O., Rupp, A. A., & Wilhelm, O. (2009). A practical illustration of multidimensional diagnostic skills profiling: Comparing results from confirmatory factor analysis and diagnostic classification models. *Studies in Educational Evaluation*, 35, 64–70.
- von Davier, M. (2005). *A general diagnostic model applied to language testing data*. ETS Research Report RR-05-16. ETS, Princeton, NJ: ETS.

## See Also

This function is used in [din](#), [gdina](#) and [gdm](#).

---

itemfit.sx2

*S-X2 Item Fit Statistic for Dichotomous Data*

---

## Description

Computes the S-X2 item fit statistic (Orlando & Thissen; 2000, 2003) for dichotomous data. Note that completely observed data is necessary for applying this function.

## Usage

```
itemfit.sx2(object, Eik_min=1, progress=TRUE)
```

```
## S3 method for class 'itemfit.sx2'
summary(object, ...)
```

```
## S3 method for class 'itemfit.sx2'
plot(x, ask=TRUE, ...)
```

## Arguments

object	Object of class <a href="#">din</a> , <a href="#">gdina</a> , <a href="#">gdm</a> , <code>sirt::rasch.mm1</code> , <code>sirt::smirt</code> or <code>TAM::tam.mm1</code>
x	Object of class <a href="#">din</a> , <a href="#">gdina</a> , <a href="#">gdm</a> , <code>sirt::rasch.mm1</code> , <code>sirt::smirt</code> or <code>TAM::tam.mm1</code>
Eik_min	The minimum expected cell size for merging score groups.
progress	An optional logical indicating whether progress should be displayed.
ask	An optional logical indicating whether every item should be separately displayed.
...	Further arguments to be passed

## Details

The S-X2 item fit statistic compares observed and expected proportions  $O_{jk}$  and  $E_{jk}$  for item  $j$  and each score group  $k$  and forms a chi-square distributed statistic

$$S - X_j^2 = \sum_{k=1}^{J-1} N_k \frac{(O_{jk} - E_{jk})^2}{E_{jk}(1 - E_{jk})}$$

The degrees of freedom are  $J - 1 - P_j$  where  $P_j$  denotes the number of estimated item parameters.

**Value**

A list with following entries

itemfit.stat	Data frame containing item fit statistics
itemtable	Data frame with expected and observed proportions for each score group and each item. Beside the ordinary p value, an adjusted p value obtained by correction due to multiple testing is provided (p.ho1m, see <code>stats::p.adjust</code> ).

**Note**

This function does not work properly for multiple groups.

**Author(s)**

Alexander Robitzsch

**References**

- Li, Y., & Rupp, A. A. (2011). Performance of the S-X2 statistic for full-information bifactor models. *Educational and Psychological Measurement, 71*, 986-1005.
- Orlando, M., & Thissen, D. (2000). Likelihood-based item-fit indices for dichotomous item response theory models. *Applied Psychological Measurement, 24*, 50-64.
- Orlando, M., & Thissen, D. (2003). Further investigation of the performance of S-X2: An item fit index for use with dichotomous item response theory models. *Applied Psychological Measurement, 27*, 289-298.
- Zhang, B., & Stone, C. A. (2008). Evaluating item fit for multidimensional item response models. *Educational and Psychological Measurement, 68*, 181-196.

**Examples**

```
## Not run:
#####
# EXAMPLE 1: Items with unequal item slopes
#####

# simulate data
set.seed(9871)
I <- 11
b <- seq(-1.5, 1.5, length=I)
a <- rep(1,I)
a[4] <- .4
N <- 1000
library(sirt)
dat <- sirt::sim.raschtype( theta=stats::rnorm(N), b=b, fixed.a=a)

**** 1PL model estimated with gdm
mod1 <- CDM::gdm( dat, theta.k=seq(-6,6,len=21), irtmodel="1PL" )
summary(mod1)
# estimate item fit statistic
```

```

fitmod1 <- CDM::itemfit.sx2(mod1)
summary(fitmod1)
##      item itemindex  S-X2 df      p S-X2_df RMSEA Nscgr Npars p.holm
##  1 I0001          1  4.173  9 0.900   0.464 0.000   10    1  1.000
##  2 I0002          2 12.365  9 0.193   1.374 0.019   10    1  1.000
##  3 I0003          3  6.158  9 0.724   0.684 0.000   10    1  1.000
##  4 I0004          4 37.759  9 0.000   4.195 0.057   10    1  0.000
##  5 I0005          5 12.307  9 0.197   1.367 0.019   10    1  1.000
##  6 I0006          6 19.358  9 0.022   2.151 0.034   10    1  0.223
##  7 I0007          7 14.610  9 0.102   1.623 0.025   10    1  0.818
##  8 I0008          8 15.568  9 0.076   1.730 0.027   10    1  0.688
##  9 I0009          9  8.471  9 0.487   0.941 0.000   10    1  1.000
## 10 I0010         10  8.330  9 0.501   0.926 0.000   10    1  1.000
## 11 I0011         11 12.351  9 0.194   1.372 0.019   10    1  1.000
##
## -- Average Item Fit Statistics --
## S-X2=13.768 | S-X2_df=1.53
# -> 4th item does not fit to the 1PL model

# plot item fit
plot(fitmod1)

#### 2PL model estimated with gdm
mod2 <- CDM::gdm( dat, theta.k=seq(-6,6,len=21), irtmodel="2PL", maxiter=100 )
summary(mod2)
# estimate item fit statistic
fitmod2 <- CDM::itemfit.sx2(mod2)
summary(fitmod2)
##      item itemindex  S-X2 df      p S-X2_df RMSEA Nscgr Npars p.holm
##  1 I0001          1  4.083  8 0.850   0.510 0.000   10    2  1.000
##  2 I0002          2 13.580  8 0.093   1.697 0.026   10    2  0.747
##  3 I0003          3  6.236  8 0.621   0.780 0.000   10    2  1.000
##  4 I0004          4  6.049  8 0.642   0.756 0.000   10    2  1.000
##  5 I0005          5 12.792  8 0.119   1.599 0.024   10    2  0.834
##  6 I0006          6 14.397  8 0.072   1.800 0.028   10    2  0.648
##  7 I0007          7 15.046  8 0.058   1.881 0.030   10    2  0.639
##  [...]
##
## -- Average Item Fit Statistics --
## S-X2=10.22 | S-X2_df=1.277

#### 1PL model estimation in smirt (sirt package)
Qmatrix <- matrix(1, nrow=I, ncol=1 )
mod1a <- sirt::smirt( dat, Qmatrix=Qmatrix )
summary(mod1a)
# item fit statistic
fitmod1a <- CDM::itemfit.sx2(mod1a)
summary(fitmod1a)

#### 2PL model estimation in smirt (sirt package)
mod2a <- sirt::smirt( dat, Qmatrix=Qmatrix, est.a="2PL")
summary(mod2a)
# item fit statistic

```

```

fitmod2a <- CDM::itemfit.sx2(mod2a)
summary(fitmod2a)

#### 1PL model estimated with rasch.mml2 (in sirt)
mod1b <- sirt::rasch.mml2(dat)
summary(mod1b)
# estimate item fit statistic
fitmod1b <- CDM::itemfit.sx2(mod1b)
summary(fitmod1b)

#### 1PL estimated in TAM
library(TAM)
mod1c <- TAM::tam.mml( resp=dat )
summary(mod1c)
# item fit
summary( CDM::itemfit.sx2( mod1c ) )
# conversion to mirt object
library(sirt)
library(mirt)
cmod1c <- sirt::tam2mirt( mod1c )
# item fit in mirt
mirt::itemfit( cmod1c$mirt )

#### 2PL estimated in TAM
mod2c <- TAM::tam.mml.2pl( resp=dat )
summary(mod2c)
# item fit
summary( CDM::itemfit.sx2( mod2c ) )
# conversion to mirt object and item fit in mirt
cmod2c <- sirt::tam2mirt( mod2c )
mirt::itemfit( cmod2c$mirt )

# estimation in mirt
mod1d <- mirt::mirt( dat, 1, itemtype="Rasch" )
mirt::itemfit( mod1d ) # compute item fit

#####
# EXAMPLE 2: Item fit statistics sim.dina dataset
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

#### Model 1: DINA model (correctly specified model)
mod1 <- CDM::din( data=sim.dina, q.matrix=sim.qmatrix )
summary(mod1)
# item fit statistic
summary( CDM::itemfit.sx2( mod1 ) )
## -- Average Item Fit Statistics --
## S-X2=7.397 | S-X2_df=1.233

#### Model 2: Mixed DINA/DINO model
#### 1th item is misspecified according to DINO rule

```

```

I <- ncol(CDM::sim.dina)
rule <- rep("DINA", I )
rule[1] <- "DINO"
mod2 <- CDM::din( data=CDM::sim.dina, q.matrix=CDM::sim.qmatrix, rule=rule)
summary(mod2)
# item fit statistic
summary( CDM::itemfit.sx2( mod2 ) )
## -- Average Item Fit Statistics --
## S-X2=9.925 | S-X2_df=1.654

#### Model 3: Additive GDINA model
mod3 <- CDM::gdina( data=CDM::sim.dina, q.matrix=CDM::sim.qmatrix, rule="ACDM")
summary(mod3)
# item fit statistic
summary( CDM::itemfit.sx2( mod3 ) )
## -- Average Item Fit Statistics --
## S-X2=8.416 | S-X2_df=1.678

## End(Not run)

```

---

item\_by\_group

---

*Create Dataset with Group-Specific Items*


---

## Description

Creates a dataset with group-specific items which can be used for multiple group comparisons.

## Usage

```
item_by_group(dat, group, invariant=NULL, rm.empty=TRUE)
```

## Arguments

dat	Dataset with item responses
group	Vector of group identifiers
invariant	Optional vector of variables which should not be made group-specific, i.e. which should be treated as invariant across groups.
rm.empty	Logical indicating whether empty columns should be removed

## Value

Extended dataset with item responses

**Examples**

```
## Not run:
#####
# EXAMPLE 1: Create dataset with group-specific item responses
#####

data(data.mg, package="CDM")
dat <- data.mg

#-- create dataset with group-specific item responses
dat0 <- CDM::item_by_group( dat=dat[,paste0("I",1:5)], group=dat$group )

#-- summary statistics
summary(dat0)
colnames(dat0)

#-- set some items to invariant
invariant_items <- c("I1","I4")
dat1 <- CDM::item_by_group( dat=dat[,paste0("I",1:5)], group=dat$group,
                           invariant=invariant_items)
colnames(dat1)

## End(Not run)
```

---

logLik

*Extract Log-Likelihood*


---

**Description**

Extracts the log-likelihood from either `din`, `gdina`, `mcdina`, `slca` or `gdm` objects.

**Usage**

```
## S3 method for class 'din'
logLik(object, ...)

## S3 method for class 'gdina'
logLik(object, ...)

## S3 method for class 'mcdina'
logLik(object, ...)

## S3 method for class 'gdm'
logLik(object, ...)

## S3 method for class 'slca'
logLik(object, ...)
```



```
## S3 method for class 'reglca'
logLik(object, ...)
```

### Arguments

```
object      An object inheriting from either class din, gdina, slca, reglca or gdm.
...         Additional arguments
```

### See Also

[din](#), [gdina](#), [gdm](#), [mcdina](#), [slca](#), [reglca](#)

### Examples

```
data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

# logLik method | DINA model
d1 <- CDM::din( sim.dina, q.matrix=sim.qmatrix, rule="DINA")
summary(d1)
l1d1 <- logLik(d1)
## > l1d1
## 'log Lik.' -2042.378 (df=25)
## > attr(1d1,"df")
## [1] 25
## > attr(1d1,"nobs")
## [1] 400
nobs(l1d1)

# AIC and BIC
AIC(l1d1)
BIC(l1d1)
```

---

mcdina

*Multiple Choice DINA Model*

---

### Description

The function `mcdina` implements the multiple choice DINA model (de la Torre, 2009; see also Ozaki, 2015; Chen & Zhou, 2017) for multiple groups. Note that the dataset must contain integer values  $1, \dots, K_j$  for each item. The multiple choice DINA model assumes that each item category possesses different diagnostic capacity. Using this modeling approach, different distractors of a multiple choice item can be of different diagnostic value. The Q-matrix can also contain integer values which allows the definition of polytomous attributes.

**Usage**

```

mcdina(dat, q.matrix, group=NULL, itempars="gr", weights=NULL,
       skillclasses=NULL, zeroprob.skillclasses=NULL,
       reduced.skillspace=TRUE, conv.crit=1e-04,
       dev.crit=0.1, maxit=1000, progress=TRUE)

## S3 method for class 'mcdina'
summary(object, digits=4, file=NULL, ...)

## S3 method for class 'mcdina'
print(x, ...)

```

**Arguments**

<code>dat</code>	A required $N \times J$ data matrix containing integer responses (1, 2, ..., $K$ ) of $N$ respondents to $J$ test items.
<code>q.matrix</code>	A required matrix specifying which item category is intended to measure which skill. The Q-matrix has $K + 2$ columns for a model with $K$ skills. In the first column should be the item index, in the second column the category integer and the rest of the columns contains the 'ordinary' Q-matrix specification. See <code>data.cdm01\$q.matrix</code> for the layout of such a Q-matrix.
<code>group</code>	An optional vector of group identifiers for multiple group estimation.
<code>itempars</code>	A character or a character vector of length $J$ indicating whether item parameters should separately estimated within each group. The default is "gr", for group-invariant item parameters choose "jo".
<code>weights</code>	An optional vector of sample weights.
<code>skillclasses</code>	An optional matrix for determining the skill space. The argument can be used if a user wants less than the prespecified number of $2^K$ skill classes.
<code>zeroprob.skillclasses</code>	An optional vector of integers which indicates which skill classes should have zero probability. Default is NULL (no skill classes with zero probability).
<code>reduced.skillspace</code>	An optional logical indicating whether the skill space should be reduced to cover only bivariate associations among skills (see Xu & von Davier, 2008).
<code>conv.crit</code>	Convergence criterion for change in item parameter values
<code>dev.crit</code>	Convergence criterion for change in deviance values
<code>maxit</code>	Maximum number of iterations.
<code>progress</code>	An optional logical indicating whether the function should print the progress of iteration in the estimation process.
<code>object</code>	Object of class <code>mcdina</code> .
<code>digits</code>	Number of digits to display in <code>summary.mcdina</code>
<code>file</code>	Optional file name for a file in which summary should be sinked.
<code>x</code>	Object of class <code>mcdina</code>
<code>...</code>	Further arguments to be passed.

## Details

The multiple choice DINA model defines for each item category  $jc$  the necessary skills to master this attribute. Therefore, the vector of skills  $\alpha$  is transformed into item-specific latent responses  $\eta_j$  which are functions of  $\alpha$  and Q-matrix entries  $q_{jc}$  (just like in the DINA model). If there are  $K_j$  item categories for item  $j$ , then there exist at most  $K_j$  values of the latent response  $\eta_j$ .

The multiple choice DINA model estimates the item response function as

$$P(X_{nj} = k | \eta_{nj} = l) = p_{jkl}$$

with the constraint  $\sum_k p_{jkl} = 1$ .

## Value

A list with following entries

item	Data frame with item parameters
posterior	Individual posterior distribution
likelihood	Individual likelihood
ic	List with information criteria
q.matrix	Used Q-matrix
pik	Array of item-category probabilities
delta	Array of item parameters
se.delta	Array of standard errors of item parameters
itemstat	Data frame containing item definitions
n.ik	Array of expected counts
deviance	Deviance
attribute.patt	Probabilities of latent classes
attribute.patt.splitted	Splitted attribute pattern
skill.patt	Marginal skill probabilities
MLE.class	Classified skills for each student (MLE)
MAP.class	Classified skills for each student (MAP)
EAP.class	Classified skills for each student (EAP)
dat	Used dataset
skillclasses	Used skill classes
group	Used group identifiers
lc	Data frame containing definitions of each item category
lr	Data frame containing the relation of each latent class and each item category
iter	Number of iterations
itempars	Used specification of item parameter estimation type
converged	Logical indicating whether convergence was achieved.

**Note**

If `dat` and `q.matrix` correspond to the 'ordinary format' which is used in `gdina`, then the function `mcdina` will detect it and convert it into the necessary format (see Example 2).

**References**

- Chen, J., & Zhou, H. (2017) Test designs and modeling under the general nominal diagnosis model framework. *PLoS ONE* 12(6), e0180016.
- de la Torre, J. (2009). A cognitive diagnosis model for cognitively based multiple-choice options. *Applied Psychological Measurement*, 33, 163-183.
- Ozaki, K. (2015). DINA models for multiple-choice items with few parameters: Considering incorrect answers. *Applied Psychological Measurement*, 39(6), 431-447.
- Xu, X., & von Davier, M. (2008). *Fitting the structured general diagnostic model to NAEP data*. ETS Research Report ETS RR-08-27. Princeton, ETS.

**See Also**

See [din](#) for estimating the DINA/DINO model and [gdina](#) for estimating the GDINA model.

**Examples**

```
#####
# EXAMPLE 1: Multiple choice DINA model for data.cdm01 dataset
#####

data(data.cdm01, package="CDM")

dat <- data.cdm01$data
group <- data.cdm01$group
q.matrix <- data.cdm01$q.matrix

### Model 1: Single group model
mod1 <- CDM::mcdina( dat=dat, q.matrix=q.matrix )
summary(mod1)

### Model 2: Multiple group model with group-invariant item parameters
mod2 <- CDM::mcdina( dat=dat, q.matrix=q.matrix, group=group, itempars="jo")
summary(mod2)

## Not run:
### Model 3: Multiple group model with group-specific item parameters
mod3 <- CDM::mcdina( dat=dat, q.matrix=q.matrix, group=group, itempars="gr")
summary(mod3)

### Model 4: Multiple group model with some group-specific item parameters
itempars <- rep("jo", ncol(dat))
itempars[ c( 2, 7, 9) ] <- "gr" # set items 2,7 and 9 group specific
mod4 <- CDM::mcdina( dat=dat, q.matrix=q.matrix, group=group, itempars=itempars)
summary(mod4)
```

```

#### Model 5: Reduced skill space

# define skill classes
skillclasses <- scan(nlines=1) # read only one line
  0 0 0  1 0 0  0 1 0  0 0 1  1 1 0  1 1 1
skillclasses <- matrix( skillclasses, ncol=3, byrow=TRUE )
mod5 <- CDM::mcdina( dat, q.matrix=q.matrix, group=group0, skillclasses=skillclasses )
summary(mod5)

#### Model 6: Reduced skill space with setting zero probabilities
#           for some latent classes

# set probabilities of classes P101 P011 (6th and 7th class) to zero
zeroprob.skillclasses <- c(6,7)
mod6 <- CDM::mcdina( dat, q.matrix, group=group, zeroprob.skillclasses=zeroprob.skillclasses )
summary(mod6)

#####
# EXAMPLE 2: Using the mcdina function for estimating the DINA model
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")

# estimate the DINA model
mod <- CDM::mcdina( sim.dina, q.matrix=sim.qmatrix )
summary(mod)

#####
# EXAMPLE 3: MCDINA model with polytomous attributes
#####

data(data.cdm02, package="CDM")
dat <- data.cdm02$data
q.matrix <- data.cdm02$q.matrix

# estimate model with polytomous attribute B1
mod1 <- CDM::mcdina( dat, q.matrix=q.matrix )
summary(mod1)

## End(Not run)

```

## Description

This function computes several measures of absolute model fit and local dependence indices for dichotomous item responses which are based on comparing observed and expected frequencies of item pairs (Chen, de la Torre & Zhang, 2013; see Details).

**Usage**

```

modelfit.cor(data, posterior, probs)
modelfit.cor2(data, posterior, probs)

modelfit.cor.din( dinobj, jkunits=0 )

## S3 method for class 'modelfit.cor.din'
summary(object, ...)

```

**Arguments**

data	An $N \times I$ data frame of dichotomous item responses
posterior	A matrix containing the posterior distribution (e.g. obtained as an output of the <a href="#">din</a> function).
probs	An array of dimension [items, categories, attribute classes] containing probabilities
dinobj	An object of class <a href="#">din</a> , <a href="#">gdina</a> or <a href="#">gdm</a> (only for dichotomous item responses)
object	An object of class <a href="#">din</a> , <a href="#">gdina</a> or <a href="#">gdm</a> (only for dichotomous item responses)
jkunits	Number of Jackknife units. The default is to use 0 units (no use of jackknifing). If jackknife estimation should be employed, use (say) at least 20 jackknife units. The input <code>jkunits</code> can be also a vector of jackknife unit identifiers.
...	Further arguments to be passed

**Details**

The fit statistics are based on predictions of the pairwise table  $(X_i, X_j)$  of item responses. The  $\chi^2$  statistic  $\chi^2_{ij}$  for item pairs  $i$  and  $j$  is defined as

$$\chi^2_{ij} = \sum_{k=0}^1 \sum_{l=0}^1 \frac{(n_{ij,kl} - e_{ij,kl})^2}{e_{ij,kl}}$$

where  $n_{ij,kl}$  is the absolute frequency of  $\{X_i = k, X_j = l\}$  and  $e_{ij,kl}$  is the expected frequency using the estimated model. Note that for calculating  $e_{ij,kl}$ , individual posterior distributions are evaluated. The  $\chi^2_{ij}$  statistic is chi-square distributed with one degree of freedom and can be used for testing whether items  $i$  and  $j$  are locally dependent. To control for multiple comparisons, p-value adjustments according to the Holm and FDR method are conducted (see [stats::p.adjust](#)).

The residual covariance  $RESIDCOV$  of item pairs  $(i, j)$  is calculated as

$$RESIDCOV_{ij} = \frac{n_{ij,11}n_{ij,00} - n_{ij,10}n_{ij,01}}{n^2} - \frac{e_{ij,11}e_{ij,00} - e_{ij,10}e_{ij,01}}{n^2}$$

where  $MRESIDCOV$  is the average of all  $RESIDCOV$  statistics and is the total sample size.

The statistic  $MADcor$  denotes the average absolute deviation between observed correlations  $r_{ij}$  and model predicted correlations  $\hat{r}_{ij}$  of item pairs  $(i, j)$ :

$$MADcor = \frac{1}{J(J-1)/2} \sum_{i < j} |r_{ij} - \hat{r}_{ij}|$$

The SRMSR (standardized root mean square root of squared residuals, Maydeu-Olivares, 2013) is also based on comparing these correlations

$$SRMSR = \sqrt{\frac{1}{J(J-1)/2} \sum_{i < j} (r_{ij} - \hat{r}_{ij})^2}$$

For calculating MADQ3 and MADaQ3, residuals  $\varepsilon_{ni} = X_{ni} - e_{ni}$  of observed and expected responses for respondents  $n$  and items  $i$  are constructed. Then, the average of the absolute values of pairwise correlations of these residuals is computed for MADQ3. For MADaQ3, the average of the centered pairwise values (i.e. by subtracting the average Q3 statistic) is calculated.

The difference of Fisher transformed correlations (Chen et al., 2013) is also computed and used for assessing statistical inference.

For every of the fit statistics MADcor, MADacor, SRMSR, MX2, 100\*MADRESIDCOV and MADQ3 it holds that smaller values (values near to zero) indicate better fit.

Standard errors and confidence intervals of fit statistics are obtained by Jackknife estimation.

## Value

A list with following entries

modelfit.stat	Model fit statistics: MADcor: mean of absolute deviations in observed and expected correlations (Di-Bello, Roussos & Stout, 2007) SRMSR: standardized mean square root of squared residuals (Maydeu-Olivares, 2013; Maydeu-Olivares & Joe, 2014) MADRESIDCOV: Mean of absolute deviations of residual covariances (McDonald & Mok, 1995) MADQ3: Mean of absolute values of $Q_3$ statistic (Yen, 1984) MADaQ3: Mean of absolute values of centered $Q_3$ statistic
modelfit.test	Test of global absolute model fit using test statistics of all item pairs. The statistic $\max(X2)$ is the maximum of all $\chi_{ij}^2$ statistics accompanied with a p value obtained by the Holm procedure. A similar statistic $\text{abs}(\text{fcor})$ is created as the absolute value of the deviations of Fisher transformed correlations as used in Chen et al. (2013).
itempairs	Fit of itempairs which can be used for inspection of local dependence. The $\chi_{ij}^2$ statistic is denoted by X2 (Chen & Thissen, 1997), the statistic $r_{ij}$ based on absolute deviations of observed and predicted correlations is fcor (Chen et al., 2013).

## Note

The function does not handle sample weights properly.

The function modelfit.cor2 has the same functionality as modelfit.cor but it is much faster because it is based on **Rcpp** code.

## References

- Chen, J., de la Torre, J., & Zhang, Z. (2013). Relative and absolute fit evaluation in cognitive diagnosis modeling. *Journal of Educational Measurement*, *50*, 123-140.
- Chen, W., & Thissen, D. (1997). Local dependence indexes for item pairs using item response theory. *Journal of Educational and Behavioral Statistics*, *22*, 265-289.
- DiBello, L. V., Roussos, L. A., & Stout, W. F. (2007). Review of cognitively diagnostic assessment and a summary of psychometric models. In C. R. Rao and S. Sinharay (Eds.), *Handbook of Statistics*, Vol. 26 (pp. 979–1030). Amsterdam: Elsevier.
- Maydeu-Olivares, A. (2013). Goodness-of-fit assessment of item response theory models (with discussion). *Measurement: Interdisciplinary Research and Perspectives*, *11*, 71-137.
- Maydeu-Olivares, A., & Joe, H. (2014). Assessing approximate fit in categorical data analysis. *Multivariate Behavioral Research*, *49*, 305-328.
- McDonald, R. P., & Mok, M. M.-C. (1995). Goodness of fit in item response models. *Multivariate Behavioral Research*, *30*, 23-40.
- Yen, W. M. (1984). Effects of local item dependence on the fit and equating performance of the three-parameter logistic model. *Applied Psychological Measurement*, *8*, 125-145.

## Examples

```
## Not run:
#####
# EXAMPLE 1: Model fit for sim.dina
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")
dat <- sim.dina
q.matrix <- sim.qmatrix

**** Model 1: DINA model for DINA simulated data
mod1 <- CDM::din(dat, q.matrix=q.matrix, rule="DINA" )
fmod1 <- CDM::modelfit.cor.din(mod1, jkunits=10)
summary(fmod1)
## Test of Global Model Fit
##      type value    p
## 1  max(X2) 8.728 0.113
## 2  abs(fcor) 0.143 0.080
##
## Fit Statistics
##              est jkunits jk_est jk_se est_low est_upp
## MADcor          0.030     10 0.020 0.005  0.010  0.030
## SRMSR           0.040     10 0.023 0.006  0.011  0.035
## 100*MADRESIDCOV 0.671     10 0.445 0.125  0.200  0.690
## MADQ3           0.062     10 0.037 0.008  0.021  0.052
## MADaQ3          0.059     10 0.034 0.008  0.019  0.050

# look at first five item pairs with highest degree of local dependence
itempairs <- fmod1$itempairs
itempairs <- itempairs[ order( itempairs$X2, decreasing=TRUE ), ]
```



```

itempairs[ 1:5, c("item1","item2", "X2", "X2_p", "X2_p.holm", "Q3") ]
##      item1 item2      X2      X2_p X2_p.holm      Q3
## 29 Item5 Item8 8.728248 0.003133174 0.1127943 -0.26616414
## 32 Item6 Item8 2.644912 0.103881881 1.0000000 0.04873154
## 21 Item3 Item9 2.195011 0.138458201 1.0000000 0.05948456
## 10 Item2 Item4 1.449106 0.228671389 1.0000000 -0.08036216
## 30 Item5 Item9 1.393583 0.237800911 1.0000000 -0.01934420

#### Model 2: DINO model for DINA simulated data
mod2 <- CDM::din(dat, q.matrix=q.matrix, rule="DINO" )
fmod2 <- CDM::modelfit.cor.din(mod2, jkunits=10 ) # 10 jackknife units
summary(fmod2)
## Test of Global Model Fit
##      type value  p
## 1 max(X2) 13.139 0.010
## 2 abs(fcor) 0.199 0.001
##
## Fit Statistics
##      est jkunits jk_est jk_se est_low est_upp
## MADcor      0.056     10 0.041 0.007 0.026 0.055
## SRMSR      0.072     10 0.045 0.019 0.007 0.083
## 100*MADRESIDCOV 1.225     10 0.878 0.183 0.519 1.236
## MADQ3      0.073     10 0.055 0.012 0.031 0.080
## MADaQ3      0.073     10 0.066 0.012 0.042 0.089

#### Model 3: estimate DINA model with gdina function
mod3 <- CDM::gdina( dat, q.matrix=q.matrix, rule="DINA" )
fmod3 <- CDM::modelfit.cor.din( mod3, jkunits=0 ) # no Jackknife estimation
summary(fmod3)
## Test of Global Model Fit
##      type value  p
## 1 max(X2) 8.756 0.111
## 2 abs(fcor) 0.143 0.078
##
## Fit Statistics
##      est
## MADcor      0.030
## SRMSR      0.040
## MX2      0.719
## 100*MADRESIDCOV 0.668
## MADQ3      0.062
## MADaQ3      0.059

#####
# EXAMPLE 2: Simulated Example DINA model
#####

set.seed(9765)
# specify Q-matrix
Q <- matrix( c(1,0, 0,1, 1,1 ), nrow=3, ncol=2, byrow=TRUE )
q.matrix <- Q[ rep(1:3,4), ]
I <- nrow(q.matrix)

```

```

# simulate data
guess <- stats::runif(I, 0, .3 )
slip <- stats::runif( I, 0, .4 )
N <- 150 # number of persons
dat <- CDM::sim.din( N=N, q.matrix=q.matrix, slip=slip, guess=guess )$dat

#### estimate DINA model
mod1 <- CDM::din( dat, q.matrix=q.matrix, rule="DINA" )
fmod1 <- CDM::modelfit.cor.din(mod1, jkunits=10)
summary(fmod1)
## Test of Global Model Fit
##      type value    p
## 1  max(X2) 10.697 0.071
## 2  abs(fcor) 0.277 0.026
##
## Fit Statistics
##      est jkunits jk_est jk_se est_low est_upp
## MADcor      0.052     10 0.026 0.010  0.006  0.045
## SRMSR      0.074     10 0.048 0.013  0.022  0.074
## 100*MADRESIDCOV 1.259     10 0.646 0.213  0.228  1.063
## MADQ3      0.080     10 0.047 0.010  0.027  0.068
## MADaQ3     0.079     10 0.046 0.010  0.027  0.065

## End(Not run)

```

---

numerical\_Hessian

*Numerical Computation of the Hessian Matrix*


---

## Description

Computes numerically the Hessian matrix of a given function for all coordinates (`numerical_Hessian`), for a selected direction (`numerical_Hessian_partial`) or the gradient of a multivariate function (`numerical_gradient`).

## Usage

```
numerical_Hessian(par, FUN, h=1e-05, gradient=FALSE,
                 hessian=TRUE, diag_only=FALSE, ...)
```

```
numerical_Hessian_partial(par, FUN, h=1e-05, coordinate=1, ...)
```

```
numerical_gradient(par, FUN, h=1E-5, ...)
```

## Arguments

`par`                   Parameter vector

`FUN`                   Specified function with argument vector `x`

h	Numerical differentiation parameter. Can be also a vector. The increment in the numerical approximation of the derivative is defined as $h_i \max(1, \theta_i)$ where $\theta_i$ denotes the $i$ th parameter.
gradient	Logical indicating whether the gradient should be calculated.
hessian	Logical indicating whether the Hessian matrix should be calculated.
diag_only	Logical indicating whether only the diagonal of the hessian should be computed.
...	Further arguments to be passed to FUN.
coordinate	Coordinate index for partial derivative

**Value**

Gradient vector or Hessian matrix or a list of both elements

**See Also**

See the **numDeriv** package and the `mirt::numerical_deriv` function from the **mirt** package.

**Examples**

```
#####
# EXAMPLE 1: Toy example for Hessian matrix
#####

# define function
f <- function(x){
  3*x[1]^3 - 4*x[2]^2 - 5*x[1]*x[2] + 10 * x[1] * x[3]^2 + 6*x[2]*sqrt(x[3])
}
# define point for evaluating partial derivatives
par <- c(3,8,4)

#--- compute gradient
CDM::numerical_Hessian( par=par, FUN=f, gradient=TRUE, hessian=FALSE)
## Not run:
mirt::numerical_deriv(par=par, f=f, gradient=TRUE)

#--- compute Hessian matrix
CDM::numerical_Hessian( par=par, FUN=f )
mirt::numerical_deriv(par=par, f=f, gradient=FALSE)
numerical_Hessian( par=par, FUN=f, h=1E-4 )

#--- compute gradient and Hessian matrix
CDM::numerical_Hessian( par=par, FUN=f, gradient=TRUE, hessian=TRUE)

## End(Not run)
```

---

osink

*Opens and Closes a sink Connection*

---

### Description

Opens and closes a sink connection.

### Usage

```
osink(file, suffix, append=FALSE)
```

```
csink(file)
```

### Arguments

file	File name. No sink is done if it has the value NULL.
suffix	Suffix which should be put next to the file name
append	Optional logical indicating whether console output should be appended to an already existing file. See argument append in <a href="#">base::sink</a> .

### See Also

[base::sink](#)

### Examples

```
## The function 'osink' is currently defined as
function (file, suffix){
  if (!is.null(file)) {
    base::sink(paste0(file, suffix), split=TRUE)
  }
}
```

```
## The function 'csink' is currently defined as
function (file){
  if (!is.null(file)) {
    base::sink()
  }
}
```

---

 personfit.appropriateness

*Appropriateness Statistic for Person Fit Assessment*


---

## Description

This function computes the person fit appropriateness statistics (Levine & Drasgow, 1988) as proposed for cognitive diagnostic models by Liu, Douglas and Henson (2009). The appropriateness statistic assesses spuriously high scorers (`attr.type=1`) and spuriously low scorers (`attr.type=0`).

## Usage

```
personfit.appropriateness(data, probs, skillclassprobs, h=0.001, eps=1e-10,
  maxiter=30, conv=1e-05, max.increment=0.1, progress=TRUE)

## S3 method for class 'personfit.appropriateness'
summary(object, digits=3, ...)

## S3 method for class 'personfit.appropriateness'
plot(x, cexpch=.65, ...)
```

## Arguments

<code>data</code>	Data frame of dichotomous item responses
<code>probs</code>	Probabilities evaluated at skill space (abilities $\theta$ )
<code>skillclassprobs</code>	Probabilities of skill classes
<code>h</code>	Numerical differentiation parameter
<code>eps</code>	Constant which is added to probabilities avoiding zero probability
<code>maxiter</code>	Maximum number of iterations
<code>conv</code>	Convergence criterion
<code>max.increment</code>	Maximum increment in iteration
<code>progress</code>	Optional logical indicating whether iteration progress should be displayed.
<code>object</code>	Object of class <code>personfit.appropriateness</code>
<code>digits</code>	Number of digits for rounding
<code>x</code>	Object of class <code>personfit.appropriateness</code>
<code>cexpch</code>	Point size in plot
<code>...</code>	Further arguments to be passed

**Value**

List with following entries

summary            Summaries of person fit statistic  
 personfit.appr.type1  
                   Statistic for spuriously high scorers (appr.type=1) evaluated for every person.  
 personfit.appr.type0  
                   Statistic for spuriously low scorers (appr.type=0) evaluated for every person.

**References**

Levine, M. V., & Drasgow, F. (1988). Optimal appropriateness measurement. *Psychometrika*, 53, 161-176.  
 Liu, Y., Douglas, J. A., & Henson, R. A. (2009). Testing person fit in cognitive diagnosis. *Applied Psychological Measurement*, 33(8), 579-598.

**Examples**

```
#####
# EXAMPLE 1: DINA model data.ecpe
#####

data(data.ecpe, package="CDM")

# fit DINA model
mod1 <- CDM::din( CDM::data.ecpe$data[,-1], q.matrix=CDM::data.ecpe$q.matrix )
summary(mod1)

# person fit appropriateness statistic
data <- mod1$data
probs <- mod1$pjk
skillclassprobs <- mod1$attribute.patt[,1]
res <- CDM::personfit.appropriateness( data, probs, skillclassprobs, maxiter=8)
# only few iterations

summary(res)
plot(res)

## Not run:
#####
# EXAMPLE 2: Person fit 2PL model
#####

data(data.read, package="sirt")
dat <- data.read
I <- ncol(dat)

# fit 2PL model
mod1 <- sirt::rasch.mml2( dat, est.a=1:I)
# person fit statistic
data <- mod1$dat
probs0 <- t(mod1$pjk)
```

```

probs <- array( 0, dim=c( I, 2, dim(probs0)[2] ) )
probs[,2,] <- probs0
probs[,1,] <- 1 - probs0
skillclassprobs <- mod1$trait.distr$pi.k
res <- CDM::personfit.appropriateness( data, probs, skillclassprobs )
summary(res)
plot(res)

## End(Not run)

```

plot.din

*Plot Method for Objects of Class din***Description**

S3 method to plot objects of the class din.

**Usage**

```

## S3 method for class 'din'
plot(x, items=c(1:ncol(x$data)), pattern="",
      uncertainty=0.1, top.n.skill.classes=6, pdf.file="",
      hide.obs=FALSE, display.nr=1:4, ask=TRUE, ...)

```

**Arguments**

x	A required object of class din, obtained from a call to the function <a href="#">din</a> .
items	An index vector giving the items to be visualized in the first plot, see ‘Details’. The default is <code>items=c(1:ncol(x\$data))</code> , which is all items.
pattern	An optional character or a numeric vector specifying a response pattern of an respondent, whose attributes are analyzed in a separate graphic. It is required to choose a pattern from the empirical data set (see Example).
uncertainty	A numeric between 0 and 0.5 giving the uncertainty bounds for deriving the observed skill occurrence probabilities in plot 2 and the simplified deterministic attribute profiles in plot 4.
top.n.skill.classes	A numeric, specifying the number of skill classes, starting with the most frequent, to be labeled in plot 3. Default value is 6.
pdf.file	An optional character string. If specified the graphics obtained from the function <code>plot.din</code> are provided in a pdf file. The default is <code>pdf.file=""</code> , which is not providing a pdf file. Otherwise specify a directory and filename ending with <code>.pdf</code> where to write the document.
hide.obs	An optional logical value. If set to TRUE, the polygonal chain for observed frequencies of skill class probabilities in the second graphic is not displayed.
display.nr	An optional numeric or numeric vector. If specified, only the plots in <code>display.nr</code> are displayed. Default is <code>display.nr=1:4</code> causing the display of all four plots.

ask	An optional logical indicating whether a request for a user input is necessary before the next figure is drawn.
...	Optional graphical parameters to be passed to or from other methods will be ignored.

### Details

The plot method graphs the results obtained from a CDM analysis. Four graphics to analyze the fitted model are produced, respectively.

The first graphic depicts the parameter estimates their diagnostic accuracy for each of chosen the items in `items`. Parameter estimates are splitted in guessing and slipping errors for each item. See [din](#) for further information.

The second graphic shows the estimated occurrence probabilities of the attributes underlying the items.

The third graphic illustrates the distribution of the skill class occurrence probabilities. The `top.n.skill.classes` most frequent skill classes are labeled.

The forth plot is a parallel coordinate plot of the individual skill profiles. Each line represents an individual skill profile. For each of these skill profiles on the vertical lines the individual probabilities of mastering the corresponding attributes are drawn.

If in `pattern` an empirical response pattern is specified, the fifth plot shows the individual skill profile of an examinee having this response pattern. For each attribute, having a mastering probability below  $0.5 - \textit{uncertainty}$  the examinee is classified as non-master of the corresponding attribute. For mastering probabilities higher than  $0.5 + \textit{uncertainty}$  the examinee is classified as master of the corresponding attribute.

### Value

If the argument `x` is of required type, and if the optional arguments `items`, `uncertainty`, `top.n.skill.classes` and `pdf.file` are specified as required, the `plot.din` produces several graphics to analyze a CDM model.

### See Also

[print.din](#), the S3 method for printing objects of the class `din`; [summary.din](#), the S3 method for summarizing objects of the class `din`, which creates objects of the class `summary.din`; [print.summary.din](#), the S3 method for printing objects of the class `summary.din`; [din](#), the main function for DINA and DINO parameter estimation, which creates objects of the class `din`. See also [CDM-package](#) for general information about this package.

### Examples

```
##
## (1) examples based on dataset fractions.subtraction.data
##

data(fraction.subtraction.data)
data(fraction.subtraction.qmatrix)
```



```

## Fix the guessing parameters of items 5, 8 and 9 equal to .20
# define a constraint.guess matrix
constraint.guess <- matrix(c(5,8,9, rep(0.2, 3)), ncol=2)
fractions.dina.fixed <- CDM::din(data=fraction.subtraction.data,
  q.matrix=fraction.subtraction.qmatrix,
  constraint.guess=constraint.guess)

## The second plot shows the expected (MAP) and observed skill
## probabilities. The third plot visualizes the skill class
## occurrence probabilities; Only the 'top.n.skill.classes' most frequent
## skill classes are labeled; it is obvious that the skill class '11111111'
## (all skills are mastered) is the most probable in this population.
## The fourth plot shows the skill probabilities conditional on response
## patterns; in this population the skills 3 and 6 seem to be
## mastered easier than the others. The fifth plot shows the
## skill probabilities conditional on a specified response
## pattern; it is shown whether a skill is mastered (above
## .5+'uncertainty') unclassifiable (within the boundaries) or
## not mastered (below .5-'uncertainty'). In this case, the
## 527th respondent was chosen; if no response pattern is
## specified, the plot will not be shown (of course)
pattern <- paste(fraction.subtraction.data[527, ], collapse="")
plot(fractions.dina.fixed, pattern=pattern, display.nr=4)

# It is also possible to input a vector of item responses
plot(fractions.dina.fixed, pattern=fraction.subtraction.data[527, ],display.nr=4)

#uncertainty=0.1, top.n.skill.classes=6 are default
plot(fractions.dina.fixed, uncertainty=0.1, top.n.skill.classes=6,
  pattern=pattern)

```

---

plot\_item\_mastery      *S3 Methods for Plotting Item Probabilities*

---

## Description

This S3 method plots item probabilities for non-masters and masters of an item.

## Usage

```

plot_item_mastery(object, pch=c(16,17), lty=c(1,2), ...)

## S3 method for class 'din'
plot_item_mastery(object, pch=c(16,17), lty=c(1,2), ...)

## S3 method for class 'gdina'
plot_item_mastery(object, pch=c(16,17), lty=c(1,2), ...)

```

**Arguments**

object	Object of classes <a href="#">din</a> or <a href="#">gdina</a>
pch	Point symbols for both groups
lty	Line symbols for both groups
...	More arguments to be passed.

**Value**

Plot

**See Also**

Plot functions for item response curves: [IRT.irfprobPlot](#).

**Examples**

```
## Not run:
#####
# EXAMPLE 1: Plot item mastery
#####

data(sim.dina)
data(sim.qmatrix)

#* estimate DINA Model
mod1 <- CDM::din(sim.dina, q.matrix=sim.qmatrix, rule="DINA")
#* estimate GDINA model
mod2 <- CDM::gdina(sim.dina, q.matrix=sim.qmatrix)

#* plots
plot_item_mastery(mod1)
plot_item_mastery(mod2)

## End(Not run)
```

---

predict	<i>Expected Values and Predicted Probabilities from Item Response Response Models</i>
---------	---

---

**Description**

This function computes expected values for each person and each item based on the individual posterior distribution. The output of this function can be the basis of creating item and person fit statistics.

**Usage**

```
IRT.predict(object, dat, group=1)

## S3 method for class 'din'
predict(object, group=1, ...)

## S3 method for class 'gdina'
predict(object, group=1, ...)

## S3 method for class 'mcdina'
predict(object, group=1, ...)

## S3 method for class 'gdm'
predict(object, group=1, ...)

## S3 method for class 'slca'
predict(object, group=1, ...)
```

**Arguments**

object	Object for the S3 methods <code>IRT.irfprob</code> and <code>IRT.posterior</code> are defined. In the <b>CDM</b> packages, these are the objects of class <code>din</code> , <code>gdina</code> , <code>mcdina</code> , <code>slca</code> or <code>gdm</code> .
dat	Dataset with item responses
group	Group index for use
...	Further arguments to be passed.

**Value**

A list with following entries

expected	Array with expected values (persons $\times$ classes $\times$ items)
probs.categ	Array with expected probabilities for each category (persons $\times$ categories $\times$ classes $\times$ items)
variance	Array with variance in predicted values for each person and each item.
residuals	Array with residuals for each person and each item
stand.resid	Array with standardized residuals for each person and each item

**Examples**

```
## Not run:
#####
# EXAMPLE 1: Fitted Rasch model in TAM package
#####

#--- Model 1: Rasch model
library(TAM)
```

```

mod1 <- TAM::tam.mml(resp=TAM::sim.rasch)
# apply IRT.predict function
prmod1 <- CDM::IRT.predict(mod1, mod1$resp )
str(prmod1)

## End(Not run)

#####
# EXAMPLE 2: Predict function for din
#####

# DINA Model
mod1 <- CDM::din( CDM::sim.dina, q.matr=CDM::sim.qmatrix, rule="DINA" )
summary(mod1)
# apply predict method
prmod1 <- CDM::IRT.predict( mod1, sim.dina )
str(prmod1)

```

---

`print.summary.din`      *Print Method for Objects of Class `summary.din`*

---

## Description

S3 method to print objects of the class `summary.din`.

## Usage

```
## S3 method for class 'summary.din'
print(x, ...)
```

## Arguments

`x`                    A required object of class `summary.din`, obtained from a call to the function `summary.din` (through generic function `summary`).

`...`                Optional parameters to be passed to or from other methods will be ignored.

## Details

The `print` method prints the summary information about objects of the class `din` computed by `summary.din`, which are the item discriminations indices, the most frequent skill classes and the model information criteria AIC and BIC. Specific summary information details such as individual items with their discrimination index can be accessed through assignment (see ‘Examples’).

## Value

If the argument `x` is of required type, `print.summary.din` prints the summary information in ‘Details’, and invisibly returns `x`.

**See Also**

[plot.din](#), the S3 method for plotting objects of the class `din`; [print.din](#), the S3 method for printing objects of the class `din`; [summary.din](#), the S3 method for summarizing objects of the class `din`, which creates objects of the class `summary.din`; [din](#), the main function for DINA and DINO parameter estimation, which creates objects of the class `din`. See also [CDM-package](#) for general information about this package.

**Examples**

```
##
## (1) examples based on dataset fractions.subtraction.data
##

## In particular, accessing detailed summary through assignment
mod <- CDM::din(data=CDM::fraction.subtraction.data,
               q.matrix=CDM::fraction.subtraction.qmatrix, rule="DINA")
smod <- summary(mod)
str(smod)
```

---

reglca

*Regularized Latent Class Analysis*


---

**Description**

Estimates the regularized latent class model for dichotomous responses based on regularization methods (Chen, Liu, Xu, & Ying, 2015; Chen, Li, Liu, & Ying, 2017). The SCAD and MCP penalty functions are available.

**Usage**

```
reglca(dat, nclasses, weights=NULL, group=NULL, regular_type="scad",
       regular_lam=0, sd_noise_init=1, item_probs_init=NULL, class_probs_init=NULL,
       random_starts=1, random_iter=20, conv=1e-05, h=1e-04, mstep_iter=10,
       maxit=1000, verbose=TRUE, prob_min=.0001)
```

```
## S3 method for class 'reglca'
summary(object, digits=4, file=NULL, ...)
```

**Arguments**

<code>dat</code>	Matrix with dichotomous item responses. NAs are allowed.
<code>nclasses</code>	Number of classes
<code>weights</code>	Optional vector of sampling weights
<code>group</code>	Optional vector for grouping variable
<code>regular_type</code>	Regularization type. Can be <code>scad</code> or <code>mcp</code> . See <a href="#">gdina</a> for more information.
<code>regular_lam</code>	Regularization parameter $\lambda$

sd_noise_init	Standard deviation for amount of noise in generating random starting values
item_probs_init	Optional matrix of initial item response probabilities
class_probs_init	Optional vector of class probabilities
random_starts	Number of random starts
random_iter	Number of initial iterations for random starts
conv	Convergence criterion
h	Numerical differentiation parameter
mstep_iter	Number of iterations in the M-step
maxit	Maximum number of iterations
verbose	Logical indicating whether convergence progress should be displayed
prob_min	Lower bound for probabilities in estimation
object	A required object of class <code>gdina</code> , obtained from a call to the function <code>gdina</code> .
digits	Number of digits after decimal separator to display.
file	Optional file name for a file in which summary should be sinked.
...	Further arguments to be passed.

### Details

The regularized latent class model for dichotomous item responses assumes  $C$  latent classes. The item response probabilities  $P(X_i = 1|c) = p_{ic}$  are estimated in such a way such that the number of different  $p_{ic}$  values per item is minimized. This approach eases interpretability and enables to recover the structure of a true (but unknown) cognitive diagnostic model.

### Value

A list containing following elements (selection):

item_probs	Item response probabilities
class_probs	Latent class probabilities
p.aj.xi	Individual posterior
p.xi.aj	Individual likelihood
loglike	Log-likelihood value
Npars	Number of estimated parameters
Nskillpar	Number of skill class parameters
G	Number of groups
n.ik	Expected counts
Nipar	Number of item parameters
n_reg	Number of regularized parameters
n_reg_item	Number of regularized parameters per item
item	Data frame with item parameters
pjk	Item response probabilities (in an array)
N	Number of persons
I	Number of items

## References

Chen, Y., Liu, J., Xu, G., & Ying, Z. (2015). Statistical analysis of Q-matrix based diagnostic classification models. *Journal of the American Statistical Association*, *110*, 850-866.

Chen, Y., Li, X., Liu, J., & Ying, Z. (2017). Regularized latent class analysis with application in cognitive diagnosis. *Psychometrika*, *82*, 660-692.

## See Also

See also the [gdina](#) and [slca](#) functions for regularized estimation.

## Examples

```
## Not run:
#####
# EXAMPLE 1: Estimating a regularized LCA for DINA data
#####

#---- simulate data
I <- 12 # number of items
# define Q-matrix
q.matrix <- matrix(0,I,2)
q.matrix[ 1:(I/3), 1 ] <- 1
q.matrix[ I/3 + 1:(I/3), 2 ] <- 1
q.matrix[ 2*I/3 + 1:(I/3), c(1,2) ] <- 1
N <- 1000 # number of persons
guess <- rep(seq(.1,.3,length=I/3), 3)
slip <- .1
rho <- 0.3 # skill correlation
set.seed(987)
dat <- CDM::sim.din( N=N, q.matrix=q.matrix, guess=guess, slip=slip,
                    mean=0*c( .2, -.2 ), Sigma=matrix( c( 1, rho,rho,1), 2, 2 ) )
dat <- dat$dat

#--- Model 1: Four latent classes without regularization
mod1 <- CDM::reglca(dat=dat, nclasses=4, regular_lam=0, random_starts=3,
                  random_iter=10, conv=1E-4)
summary(mod1)

#--- Model 2: Four latent classes with regularization and lambda=.08
mod2 <- CDM::reglca(dat=dat, nclasses=4, regular_lam=0.08, regular_type="scad",
                  random_starts=3, random_iter=10, conv=1E-4)
summary(mod2)

#--- Model 3: Four latent classes with regularization and lambda=.05 with warm start

# "warm start" -> use initial parameters from fitted model with higher lambda value
item_probs_init <- mod2$item_probs
class_probs_init <- mod2$class_probs
mod3 <- CDM::reglca(dat=dat, nclasses=4, regular_lam=0.05, regular_type="scad",
                  item_probs_init=item_probs_init, class_probs_init=class_probs_init,
                  random_starts=3, random_iter=10, conv=1E-4)
```

```
## End(Not run)
```

---

sequential.items	<i>Constructing a Dataset with Sequential Pseudo Items for Ordered Item Responses</i>
------------------	---

---

## Description

This function constructs dichotomous pseudo items from polytomous ordered items (Tutz, 1997). Using this method, developed test models for dichotomous data can be applied for polytomous item responses after transforming them into dichotomous data. See Details for the construction.

Ma and de la Torre (2016) proposed a sequential GDINA model. Interestingly, the proposed model can be fitted with the `gdina` function in this **CDM** package while item responses has to be transformed with the `sequential.items` function for obtaining dichotomous pseudoitems. The Q-matrix for the sequential model of Ma and de la Torre (2016) can be used in the GDINA model for the dichotomous pseudoitems. This approach is implemented for automatic use in [gdina](#).

## Usage

```
sequential.items(data)
```

## Arguments

data	A data frame with item responses
------	----------------------------------

## Details

Assume that item  $j$  possesses  $K \geq 3$  categories. We label these categories as  $k = 0, 1, \dots, K - 1$ . The original item responses  $X_{nj}$  for person  $n$  at item  $j$  is then transformed into  $K - 1$  pseudo items  $Y_{j1}, \dots, Y_{j,K-1}$ .

The first pseudo item response  $Y_{nj1}$  is defined as 1 iff  $X_{nj} \geq 1$ . The second item responses  $Y_{nj2}$  is 1 iff  $X_{nj} \geq 2$ , it is 0 iff  $X_{nj} = 1$  and it is missing (NA in the dataset) iff  $X_{nj} = 0$ . The construction proceeds in the same manner for other categories (see Tutz, 1997). The pseudo items can be recognized as 'hurdles' a participant has to master to get a score of  $k$  for the original item.

The pseudo items are treated as conditionally independent which implies that IRT models or CDMs which assume local independence can be employed for estimation.

For deriving item response probabilities of the original items from response probabilities of the pseudo items see Tutz (1997, p. 141ff.).

## Value

A list with following entries

<code>dat.expand</code>	A data frame with dichotomous pseudo items
<code>iteminfo</code>	A data frame containing some item information
<code>maxK</code>	Vector with maximum number of categories per item



## References

Ma, W., & de la Torre, J. (2016). A sequential cognitive diagnosis model for polytomous responses. *British Journal of Mathematical and Statistical Psychology*, 69(3), 253-275.

Tutz, G. (1997). Sequential models for ordered responses. In W. van der Linden & R. K. Hambleton. *Handbook of modern item response theory* (pp. 139-152). New York: Springer.

## Examples

```
#####
# EXAMPLE 1: Constructing sequential pseudo items for data.mg
#####

data(data.mg, package="CDM")
dat <- data.mg
items <- colnames(dat)[ which( substring( colnames(dat),1,1)=="I" ) ]
## [1] "I1" "I2" "I3" "I4" "I5" "I6" "I7" "I8" "I9" "I10" "I11"
data <- dat[,items]

# construct sequential dichotomous pseudo items
res <- CDM::sequential.items(data)

# item information table
res$iteminfo
##      item itemindex category pseudoitem
##  1    I1           1         1         I1
##  2    I2           2         1         I2
##  3    I3           3         1         I3
##  4    I4           4         1    I4_Cat1
##  5    I4           4         2    I4_Cat2
##  6    I5           5         1    I5_Cat1
##  7    I5           5         2    I5_Cat2
##    [...]

# extract dataset with pseudo items
dat.expand <- res$dat.expand
colnames(dat.expand)
## [1] "I1" "I2" "I3" "I4_Cat1" "I4_Cat2" "I5_Cat1"
## [7] "I5_Cat2" "I6_Cat1" "I6_Cat2" "I7_Cat1" "I7_Cat2" "I7_Cat3"
## [13] "I8" "I9" "I10" "I11_Cat1" "I11_Cat2" "I11_Cat3"

# compare original items and pseudoitems

##### Item I1
stats::xtabs( ~ paste(data$I1) + paste(dat.expand$I1) )
##          paste(dat.expand$I1)
##  paste(data$I1)    0    1    NA
##           0  4339    0    0
##           1    0 33326    0
##           NA    0    0  578

##### Item I7
```

```

stats::xtabs( ~ paste(data$I7) + paste(dat.expand$I7_Cat1) )
##           paste(dat.expand$I7_Cat1)
##  paste(data$I7)    0    1   NA
##           0  3825    0    0
##           1    0 14241    0
##           2    0 14341    0
##           3    0  5169    0
##           NA    0    0   667

stats::xtabs( ~ paste(data$I7) + paste(dat.expand$I7_Cat2) )
##           paste(dat.expand$I7_Cat2)
##  paste(data$I7)    0    1   NA
##           0    0    0  3825
##           1 14241    0    0
##           2    0 14341    0
##           3    0  5169    0
##           NA    0    0   667

stats::xtabs( ~ paste(data$I7) + paste(dat.expand$I7_Cat3) )
##           paste(dat.expand$I7_Cat3)
##  paste(data$I7)    0    1   NA
##           0    0    0  3825
##           1    0    0 14241
##           2 14341    0    0
##           3    0  5169    0
##           NA    0    0   667

## Not run:
###* Model 1: Rasch model for sequentially created pseudo items
mod <- CDM::gdm( dat.expand, irtmodel="1PL", theta.k=seq(-5,5,len=21),
                skillspace="normal", decrease.increments=TRUE)

## End(Not run)

```

---

sim.din

*Data Simulation Tool for DINA, DINO and mixed DINA and DINO Data*


---

## Description

sim.din can be used to simulate dichotomous response data according to a CDM model. The model type DINA or DINO can be specified item wise. The number of items, the sample size, and two parameters for each item, the slipping and guessing parameters, can be set explicitly.

## Usage

```

sim.din(N=0, q.matrix, guess=rep(0.2, nrow(q.matrix)),
        slip=guess, mean=rep(0, ncol(q.matrix)), Sigma=diag(ncol(q.matrix)),
        rule="DINA", alpha=NULL)

```

**Arguments**

N	A numeric value specifying the number $N$ of requested response patterns. If alpha is specified, then N is set by default to 0.
q.matrix	A required binary $J \times K$ matrix describing which of the $K$ attributes are required, coded by 1, and which attributes are not required, coded by 0, to master the items.
guess	An optional vector of guessing parameters. Default is 0.2 for each item.
slip	An optional vector of slipping parameters. Default is 0.2 for each item.
mean	A numeric vector of length <code>ncol(q.matrix)</code> indicating the mean vector of the continuous version of the dichotomous skill vector. Default is <code>rep(0, length=ncol(q.matrix))</code> . That is, having a probability of 0.5 for possessing each of the attributes.
Sigma	A matrix of dimension <code>ncol(q.matrix)</code> times <code>ncol(q.matrix)</code> specifying the covariance matrix of the continuous version of the dichotomous skill vector (i.e., the tetrachoric correlation of the dichotomous skill vector). Default is <code>diag(1, ncol(q.matrix))</code> . That is, by default the possession of the attributes is assumed to be uncorrelated.
rule	An optional character string or vector of character strings specifying the model rule that is used. The character strings must be of "DINA" or "DINO". If a vector of character strings is specified, implying an itemwise condensation rule, the vector must be of length $J$ , which is the number of used items. The default is the condensation rule "DINA" for all items.
alpha	A matrix of attribute patterns which can be given as an input instead of underlying latent variables. If alpha is not NULL, then mean and Sigma are ignored.

**Value**

A list with following entries

dat	A matrix of simulated dichotomous response data according to the specified CDM model.
alpha	Simulated attributes

**References**

Rupp, A. A., Templin, J. L., & Henson, R. A. (2010). *Diagnostic Measurement: Theory, Methods, and Applications*. New York: The Guilford Press.

**See Also**

[Data-sim](#) for artificial date set simulated with the help of this method; [plot.din](#), the S3 method for plotting objects of the class `din`; [summary.din](#), the S3 method for summarizing objects of the class `din`, which creates objects of the class `summary.din`; [print.summary.din](#), the S3 method for printing objects of the class `summary.din`; [din](#), the main function for DINA and DINO parameter estimation, which creates objects of the class `din`. See also [CDM-package](#) for general information about this package.

See [sim\\_model](#) for a general simulation function.

## Examples

```
#####
## EXAMPLE 1: simulate DINA/DINO data according to a tetrachoric correlation
#####

# define Q-matrix for 4 items and 2 attributes
q.matrix <- matrix(c(1,0,0,1,1,1,1,1), ncol=2, nrow=4)

# Slipping parameters
slip <- c(0.2,0.3,0.4,0.3)

# Guessing parameters
guess <- c(0,0.1,0.05,0.2)

set.seed(1567) # fix random numbers
dat1 <- CDM::sim.din(N=200, q.matrix, slip=slip, guess=guess,
  # Possession of the attributes with high probability
  mean=c(0.5,0.2),
  # Possession of the attributes is weakly correlated
  Sigma=matrix(c(1,0.2,0.2,1), ncol=2), rule="DINA")$dat
head(dat1)

set.seed(15367) # fix random numbers
res <- CDM::sim.din(N=200, q.matrix, slip=slip, guess=guess, mean=c(0.5,0.2),
  Sigma=matrix(c(1,0.2,0.2,1), ncol=2), rule="DINO")

# extract simulated data
dat2 <- res$dat
# extract attribute patterns
head( res$alpha )
##      [,1] [,2]
## [1,]  1   1
## [2,]  1   1
## [3,]  1   1
## [4,]  1   1
## [5,]  1   1
## [6,]  1   0

# simulate data based on given attributes
#      -> 5 persons with 2 attributes -> see the Q-matrix above
alpha <- matrix( c(1,0,1,0,1,1,0,1,1,1),
  nrow=5,ncol=2, byrow=TRUE )
CDM::sim.din( q.matrix=q.matrix, alpha=alpha )

## Not run:
#####
# EXAMPLE 2: Simulation based on attribute vectors
#####
set.seed(76)
# define Q-matrix
Qmatrix <- matrix(c(1,0,1,0,1,0,0,1,0,1,0,1,1,1,1,1), 8, 2, byrow=TRUE)
colnames(Qmatrix) <- c("Attr1","Attr2")
```

```

# define skill patterns
alpha.patt <- matrix(c(0,0,1,0,0,1,1,1), 4,2,byrow=TRUE )
AP <- nrow(alpha.patt)
# define pattern probabilities
alpha.prob <- c( .20, .40, .10, .30 )
# simulate alpha latent responses
N <- 1000      # number of persons
ind <- sample( x=1:AP, size=N, replace=TRUE, prob=alpha.prob)
alpha <- alpha.patt[ ind, ]      # (true) latent responses
# define guessing and slipping parameters
guess <- c(.26,.3,.07,.23,.24,.34,.05,.1)
slip <- c(.05,.16,.19,.03,.03,.19,.15,.05)
# simulation of the DINA model
dat <- CDM::sim.din(N=0, q.matrix=Qmatrix, guess=guess,
                   slip=slip, alpha=alpha)$dat
# estimate model
res <- CDM::din( dat, q.matrix=Qmatrix )
# extract maximum likelihood estimates for individual classifications
est <- paste( res$pattern$mle.est )
# calculate classification accuracy
mean( est==apply( alpha, 1, FUN=function(l1){ paste0(l1[1],l1[2] ) } ) )
## [1] 0.935

#####
# EXAMPLE 3: Simulation based on already estimated DINA model for data.ecpe
#####

dat <- CDM::data.ecpe$data
q.matrix <- CDM::data.ecpe$q.matrix

###
# (1) estimate DINA model
mod <- CDM::din( data=dat[,-1], q.matrix=q.matrix, rule="DINA")

###
# (2) simulate data according to DINA model
set.seed(977)
# number of subjects to be simulated
n <- 3000
# simulate attribute patterns
probs <- mod$attribute.patt$class.prob      # probabilities
patt <- mod$attribute.patt$split          # response patterns
alpha <- patt[ sample( 1:(length(probs) ), n, prob=probs, replace=TRUE), ]
# simulate data using estimated item parameters
res <- CDM::sim.din(N=n, q.matrix=q.matrix, guess=mod$guess$est, slip=mod$slip$est,
                   rule="DINA", alpha=alpha)
# extract data
dat <- res$dat

## End(Not run)

```

sim.gdina

*Simulation of the GDINA model***Description**

The function `sim.gdina.prepare` creates necessary design matrices  $M_j$ ,  $A_j$  and `necc.attr`. In most cases, only the list of item parameters `delta` must be modified by the user when applying the simulation function `sim.gdina`. The distribution of latent classes  $\alpha$  is represented by an underlying multivariate normal distribution  $\alpha^*$  for which a mean vector `thresh.alpha` and a covariance matrix `cov.alpha` must be specified. Alternatively, a matrix of skill classes `alpha` can be given as an input.

Note that this version of `sim.gdina` only works for dichotomous attributes.

**Usage**

```
sim.gdina(n, q.matrix, delta, link="identity", thresh.alpha=NULL,
         cov.alpha=NULL, alpha=NULL, Mj, Aj, necc.attr)
```

```
sim.gdina.prepare( q.matrix )
```

**Arguments**

<code>n</code>	Number of persons
<code>q.matrix</code>	Q-matrix (see <a href="#">sim.din</a> )
<code>delta</code>	List with $J$ entries where $J$ is the number of items. Every list element corresponds to the parameter of an item.
<code>link</code>	Link function. Choices are <code>identity</code> (default), <code>logit</code> and <code>log</code> .
<code>thresh.alpha</code>	Vector of thresholds (means) of $\alpha^*$
<code>cov.alpha</code>	Covariance matrix of $\alpha^*$
<code>alpha</code>	Matrix of skill classes if they should not be simulated
<code>Mj</code>	Design matrix, see <a href="#">gdina</a>
<code>Aj</code>	Design matrix, see <a href="#">gdina</a>
<code>necc.attr</code>	List with $J$ entries containing necessary attributes for each item

**Value**

The output of `sim.gdina` is a list with following entries:

<code>data</code>	Simulated item responses
<code>alpha</code>	Data frame with simulated attributes
<code>q.matrix</code>	Used Q-matrix
<code>delta</code>	Used delta item parameters
<code>Aj</code>	Design matrices $A_j$
<code>Mj</code>	Design matrices $M_j$

link                    Used link function

The function `sim.gdina.prepare` possesses the following values as output in a list: `delta`, `necc.attr`, `Aj` and `Mj`.

## References

de la Torre, J. (2011). The generalized DINA model framework. *Psychometrika*, 76, 179–199.

## See Also

For estimating the GDINA model see [gdina](#).

See the `GDINA::simGDINA` function in the **GDINA** package for similar functionality.

See [sim\\_model](#) for a general simulation function.

## Examples

```
#####
# EXAMPLE 1: Simulating the GDINA model
#####

n <- 50                    # number of persons
# define Q-matrix
q.matrix <- matrix( c(1,1,0, 0,1,1, 1,0,1, 1,0,0,
                    0,0,1, 0,1,0, 1,1,1, 0,1,1, 0,1,1), ncol=3, byrow=TRUE)
# thresholds for attributes alpha^ast
thresh.alpha <- c( .65, 0, -.30 )
# covariance matrix for alpha^ast
cov.alpha <- matrix(1,3,3)
cov.alpha[1,2] <- cov.alpha[2,1] <- .4
cov.alpha[1,3] <- cov.alpha[3,1] <- .6
cov.alpha[3,2] <- cov.alpha[2,3] <- .8

# prepare design matrix by applying sim.gdina.prepare function
rp <- CDM::sim.gdina.prepare( q.matrix )
delta <- rp$delta
necc.attr <- rp$necc.attr
Aj <- rp$Aj
Mj <- rp$Mj
# define delta parameters
# intercept - main effects - second order interactions - ...
str(delta) #=> modify the delta parameter list which contains only zeroes as default
## List of 9
## $ : num [1:4] 0 0 0 0
## $ : num [1:4] 0 0 0 0
## $ : num [1:4] 0 0 0 0
## $ : num [1:2] 0 0
## $ : num [1:2] 0 0
## $ : num [1:2] 0 0
## $ : num [1:8] 0 0 0 0 0 0 0 0
## $ : num [1:4] 0 0 0 0
## $ : num [1:4] 0 0 0 0
```

```

delta[[1]] <- c( .2, .1, .15, .4 )
delta[[2]] <- c( .2, .3, .3, -.2 )
delta[[3]] <- c( .2, .2, .2, 0 )
delta[[4]] <- c( .15, .6 )
delta[[5]] <- c( .1, .7 )
delta[[6]] <- c( .25, .65 )
delta[[7]] <- c( .25, .1, .1, .1, 0, 0, 0, .25 )
delta[[8]] <- c( .2, 0, .3, -.1 )
delta[[9]] <- c( .2, .2, 0, .3 )

#####
# Now, the "real simulation" starts
sim.res <- CDM::sim.gdina( n=n, q.matrix=q.matrix, delta=delta, link="identity",
                        thresh.alpha=thresh.alpha, cov.alpha=cov.alpha,
                        Mj=Mj, Aj=Aj, necc.attr=necc.attr)
# sim.res$data      # simulated data
# sim.res$alpha     # simulated alpha

## Not run:
#####
# EXAMPLE 2: Simulation based on already estimated GDINA model for data.ecpe
#####

data(data.ecpe)
dat <- data.ecpe$data
q.matrix <- data.ecpe$q.matrix

###
# (1) estimate GDINA model
mod <- CDM::gdina( data=dat[, -1], q.matrix=q.matrix )

###
# (2) simulate data according to GDINA model
set.seed(977)

# prepare design matrix by applying sim.gdina.prepare function
rp <- CDM::sim.gdina.prepare( q.matrix )
necc.attr <- rp$necc.attr

# number of subjects to be simulated
n <- 3000
# simulate attribute patterns
probs <- mod$attribute.patt$class.prob # probabilities
patt <- mod$attribute.patt$split      # response patterns
alpha <- patt[ sample( 1:(length(probs)) , n, prob=probs, replace=TRUE), ]

# simulate data using estimated item parameters
sim.res <- CDM::sim.gdina( n=n, q.matrix=q.matrix, delta=mod$delta, link="identity",
                        alpha=alpha, Mj=mod$Mj, Aj=mod$Aj, necc.attr=rp$necc.attr)
# extract data
dat <- sim.res$data

#####

```



```

# EXAMPLE 3: Simulation based on already estimated RRUM model for data.ecpe
#####

dat <- CDM::data.ecpe$data
q.matrix <- CDM::data.ecpe$q.matrix

###
# (1) estimate reduced RUM model
mod <- CDM::gdina( data=dat[,-1], q.matrix=q.matrix, rule="RRUM" )
summary(mod)

###
# (2) simulate data according to RRUM model
set.seed(977)

# prepare design matrix by applying sim.gdina.prepare function
rp <- CDM::sim.gdina.prepare( q.matrix )
necc.attr <- rp$necc.attr

# number of subjects to be simulated
n <- 5000
# simulate attribute patterns
probs <- mod$attribute.patt$class.prob # probabilities
patt <- mod$attribute.patt$splitting # response patterns
alpha <- patt[ sample( 1:(length(probs)) , n, prob=probs, replace=TRUE), ]

# simulate data using estimated item parameters
sim.res <- CDM::sim.gdina( n=n, q.matrix=q.matrix, delta=mod$delta, link=mod$link,
                          alpha=alpha, Mj=mod$Mj, Aj=mod$Aj, necc.attr=rp$necc.attr )
# extract data
dat <- sim.res$data

## End(Not run)

```

---

sim\_model

*Simulate an Item Response Model*


---

### Description

Simulates an item response model given a fitted object or input of item response probabilities and skill class probabilities.

### Usage

```

sim_model(object=NULL, irfprob=NULL, theta_index=NULL, prob.theta=NULL,
          data=NULL, N_sim=NULL )

```

**Arguments**

object	Fitted object for which the methods <code>IRT.posterior</code> , and <code>IRT.data</code> are defined.
irfprob	Array of item response function values (items $\times$ categories $\times$ skill classes)
theta_index	Skill class index for sampling
prob.theta	Skill class probabilities
data	Original dataset, only relevant for simulating item response pattern with missing values
N_sim	Number of subjects to be simulated

**Value**

	List containing elements
dat	Simulated item responses
theta	Simulated skill classes
theta_index	Corresponding indices to theta

**Examples**

```
## Not run:
#####
# EXAMPLE 1: GDINA model simulation
#####

data(sim.dina, package="CDM")
data(sim.qmatrix, package="CDM")
dat <- sim.dina
Q <- sim.qmatrix

# fit DINA model
mod <- CDM::gdina( dat, q.matrix=Q, rule="DINA")
summary(mod)

*** simulate new item responses (N equals observed sample size)
dat1 <- CDM::sim_model(mod)

*** simulate item responses for N=2000 subjects
dat2 <- CDM::sim_model(mod, N_sim=2000)
str(dat2)

*** simulate item responses based on input item response probabilities
*** and theta_index
irfprob <- CDM::IRT.irfprob(mod)
prob.theta <- attr(irfprob, "prob.theta")
TP <- length(prob.theta)
theta_index <- sample(1:TP, size=1000, prob=prob.theta, replace=TRUE )
#-- simulate
dat3 <- CDM::sim_model(irfprob=irfprob, theta_index=theta_index)
str(dat3)
```

```
## End(Not run)
```

---

```
skill.cor
```

```
Tetrachoric or Polychoric Correlations between Attributes
```

---

## Description

This function takes the results of `din` or `gdina` and computes tetrachoric or polychoric correlations between attributes (see e.g. Templin & Henson, 2006).

## Usage

```
# tetrachoric correlations
skill.cor(object)

# polychoric correlations
skill.polychor(object, colindex=1)
```

## Arguments

<code>object</code>	Object of class <code>din</code> or <code>gdina</code>
<code>colindex</code>	Index which can used for group-wise calculation of polychoric correlations

## Value

A list with following entries:

<code>conttable.skills</code>	Bivariate contingency table of all skill pairs
<code>cor.skills</code>	Tetrachoric correlation matrix for skill distribution

## References

Templin, J., & Henson, R. (2006). Measurement of psychological disorders using cognitive diagnosis models. *Psychological Methods*, *11*, 287-305.

## Examples

```
data(sim.dino, package="CDM")
data(sim.qmatrix, package="CDM")

# estimate model
d4 <- CDM::din( sim.dino, q.matrix=sim.qmatrix)
# compute tetrachoric correlations
CDM::skill.cor(d4)
## estimated tetrachoric correlations
## $cor.skills
##           V1           V2           V3
```

```
## V1 1.0000000 0.2567718 0.2552958
## V2 0.2567718 1.0000000 0.9842188
## V3 0.2552958 0.9842188 1.0000000
```

---

skillspace.approximation

*Skill Space Approximation*

---

### Description

This function approximates the skill space with  $K$  skills to approximate a (typically high-dimensional) skill space of  $2^K$  classes by  $L$  classes ( $L < 2^K$ ). The large number of latent classes are represented by underlying continuous latent variables for the dichotomous skills (see George & Robitzsch, 2014, for more details).

### Usage

```
skillspace.approximation(L, K, nmax=5000)
```

### Arguments

L	Number of skill classes used for approximation
K	Number of skills
nmax	Number of quasi-randomly generated skill classes using the QUnif function in <b>sfsmisc</b>

### Value

A matrix containing skill classes in rows

### Note

This function uses the `sfsmisc::QUnif` function from the **sfsmisc** package.

### References

George, A. C., & Robitzsch, A. (2014). Multiple group cognitive diagnosis models, with an emphasis on differential item functioning. *Psychological Test and Assessment Modeling*, 56(4), 405-432.

### See Also

See also [gdina](#) (Example 9).

## Examples

```
#####
# EXAMPLE 1: Approximate a skill space of K=8 eight skills by 20 classes
#####

#=> 2^8=256 latent classes if all latent classes would be used
CDM::skillspace.approximation( L=20, K=8 )
##           [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8]
## P00000000  0    0    0    0    0    0    0    0
## P00000001  0    0    0    0    0    0    0    1
## P00001011  0    0    0    0    1    0    1    1
## P00010011  0    0    0    1    0    0    1    1
## P00101001  0    0    1    0    1    0    0    1
## [...]
## P11011110  1    1    0    1    1    1    1    0
## P11100110  1    1    1    0    0    1    1    0
## P11111111  1    1    1    1    1    1    1    1
```

---

skillspace.hierarchy    *Creation of a Hierarchical Skill Space*

---

## Description

The function `skillspace.hierarchy` defines a reduced skill space for hierarchies in skills (see e.g. Leighton, Gierl, & Hunka, 2004). The function `skillspace.full` defines a full skill space for dichotomous skills.

## Usage

```
skillspace.hierarchy(B, skill.names)
```

```
skillspace.full(skill.names)
```

## Arguments

**B**                    A matrix or a string containing restrictions of the hierarchy. If  $B$  is a  $K \times K$  matrix containing where  $K$  denotes the number of skills, then  $B[ii, jj]=1$  means that if an examinee mastered skill  $jj$ , then he or she should also master skill  $ii$ .  
Alternatively, a string can be also conveniently used for defining a hierarchy (see Examples).

**skill.names**        Vector of names in skills

## Details

The reduced skill space output can be used as an argument in `din` or `gdina` to directly test for a hierarchy in attributes.

**Value**

A list with following entries

```
R           Reachability matrix
skillspace.reduced
              Reduced skill space fulfilling the specified hierarchy
skillspace.complete
              Complete skill space
zeroprob.skillclasses
              Indices of skill patterns in skillspace.complete which were removed for
              defining skillspace.reduced
```

**References**

Leighton, J. P., Gierl, M. J., & Hunka, S. M. (2004). The attribute hierarchy method for cognitive assessment: A variation on Tatsuoka's rule space approach. *Journal of Educational Measurement*, *41*, 205-237.

**See Also**

See [din](#) (Example 6) for an application of skillspace.hierarchy for model comparisons.  
See the [GDINA::att.structure](#) function in the **GDINA** package for similar functionality.

**Examples**

```
#####
# EXAMPLE 1: Toy example with 3 skills
#####

K <- 3 # number of skills
skill.names <- paste0("A", 1:K ) # names of skills

# create a zero matrix for hierarchy definition
B0 <- 0*diag(K)
rownames(B0) <- colnames(B0) <- skill.names

#*** Model 1: A1 > A2 > A3
B <- B0
B[1,2] <- 1 # A1 > A2
B[2,3] <- 1 # A2 > A3

sp1 <- CDM::skillspace.hierarchy( B=B, skill.names=skill.names )
sp1$skillspace.reduced
##      A1 A2 A3
##  1  0  0  0
##  2  1  0  0
##  4  1  1  0
##  8  1  1  1

#*** Model 2: A1 > A2 and A1 > A3
```

```

B <- B0
B[1,2] <- 1 # A1 > A2
B[1,3] <- 1 # A1 > A3

sp2 <- CDM::skillspace.hierarchy( B=B, skill.names=skill.names )
sp2$skillspace.reduced
##      A1 A2 A3
##    1  0  0  0
##    2  1  0  0
##    4  1  1  0
##    6  1  0  1
##    8  1  1  1

**** Model 3: A1 > A3, A2 is not included in a hierarchical way
B <- B0
B[1,3] <- 1 # A1 > A3

sp3 <- CDM::skillspace.hierarchy( B=B, skill.names=skill.names )
sp3$skillspace.reduced
##      A1 A2 A3
##    1  0  0  0
##    2  1  0  0
##    3  0  1  0
##    4  1  1  0
##    6  1  0  1
##    8  1  1  1

#~~~ Hierarchy specification using strings

**** Model 1: A1 > A2 > A3
B <- "A1 > A2
      A2 > A3"
sp1 <- CDM::skillspace.hierarchy( B=B, skill.names=skill.names )
sp1$skillspace.reduced

# Model 1 can be also written in one line for B
B <- "A1 > A2 > A3"
sp1b <- CDM::skillspace.hierarchy( B=B, skill.names=skill.names )
sp1b$skillspace.reduced

**** Model 2: A1 > A2 and A1 > A3
B <- "A1 > A2
      A1 > A3"
sp2 <- CDM::skillspace.hierarchy( B=B, skill.names=skill.names )
sp2$skillspace.reduced

**** Model 3: A1 > A3
B <- "A1 > A3"
sp3 <- CDM::skillspace.hierarchy( B=B, skill.names=skill.names )
sp3$skillspace.reduced

## Not run:
#####

```

```

# EXAMPLE 2: Examples from Leighton et al. (2004): Fig. 1 (p. 210)
#####

skill.names <- paste0("A",1:6) # 6 skills

### Model 1: Linear hierarchy (A)
B <- "A1 > A2 > A3 > A4 > A5 > A6"
sp1 <- CDM::skillspace.hierarchy( B=B, skill.names=skill.names )
sp1$skillspace.reduced

### Model 2: Convergent hierarchy (B)
B <- "A1 > A2 > A3
      A2 > A4
      A3 > A5 > A6
      A4 > A5 > A6"
sp2 <- CDM::skillspace.hierarchy( B=B, skill.names=skill.names )
sp2$skillspace.reduced

### Model 3: Divergent hierarchy (C)
B <- "A1 > A2 > A3
      A1 > A4 > A5
      A1 > A4 > A6"
sp3 <- CDM::skillspace.hierarchy( B=B, skill.names=skill.names )
sp3$skillspace.reduced

### Model 4: Unstructured hierarchy (D)
B <- "A1 > A2 \n A1 > A3 \n A1 > A4 \n A1 > A5 \n A1 > A6"
# This specification of B is equivalent to writing separate lines:
# B <- "A1 > A2
#       A1 > A3
#       A1 > A4
#       A1 > A5
#       A1 > A6"
sp4 <- CDM::skillspace.hierarchy( B=B, skill.names=skill.names )
sp4$skillspace.reduced

## End(Not run)

```

---

slca

*Structured Latent Class Analysis (SLCA)*


---

## Description

This function implements a structured latent class model for polytomous item responses (Formann, 1985, 1992). Lasso estimation for the item parameters is included (Chen, Liu, Xu & Ying, 2015; Chen, Li, Liu & Ying, 2017; Sun, Chen, Liu, Ying & Xin, 2016).

## Usage

```
slca(data, group=NULL, weights=rep(1, nrow(data)), Xdes,
```



```

Xlambda.init=NULL, Xlambda.fixed=NULL, Xlambda.constr.V=NULL,
Xlambda.constr.c=NULL, delta.designmatrix=NULL,
delta.init=NULL, delta.fixed=NULL, delta.linkfct="log",
Xlambda_positive=NULL, regular_type="lasso", regular_lam=0, regular_w=NULL,
regular_n=nrow(data), maxiter=1000, conv=1e-5, globconv=1e-5, msteps=10,
convM=5e-04, decrease.increments=FALSE, oldfac=0, dampening_factor=1.01,
seed=NULL, progress=TRUE, PEM=TRUE, PEM_itermax=maxiter, ...)

## S3 method for class 'slca'
summary(object, file=NULL, ...)

## S3 method for class 'slca'
print(x, ...)

## S3 method for class 'slca'
plot(x, group=1, ... )

```

### Arguments

<code>data</code>	Matrix of polytomous item responses
<code>group</code>	Optional vector of group identifiers. For <code>plot.slca</code> it is a single integer group identified.
<code>weights</code>	Optional vector of sample weights
<code>Xdes</code>	Design matrix for $x_{ijh}$ with $q_{ihjv}$ entries. Therefore, it must be an array with four dimensions referring to items ( $i$ ), categories ( $h$ ), latent classes ( $j$ ) and $\lambda$ parameters ( $v$ ).
<code>Xlambda.init</code>	Initial $\lambda_x$ parameters
<code>Xlambda.fixed</code>	Fixed $\lambda_x$ parameters. These must be provided by a matrix with two columns: 1st column – Parameter index, 2nd column: Fixed value.
<code>Xlambda.constr.V</code>	A design matrix for linear restrictions of the form $V_x \lambda_x = c_x$ for the $\lambda_x$ parameter.
<code>Xlambda.constr.c</code>	A vector for the linear restriction $V_x \lambda_x = c_x$ of the $\lambda_x$ parameter.
<code>delta.designmatrix</code>	Design matrix for delta parameters $\delta$ parameterizing the latent class distribution by log-linear smoothing (Xu & von Davier, 2008)
<code>delta.init</code>	Initial $\delta$ parameters
<code>delta.fixed</code>	Fixed $\delta$ parameters. This must be a matrix with three columns: 1st column: Parameter index, 2nd column: Group index, 3rd column: Fixed value
<code>delta.linkfct</code>	Link function for skill space reduction. This can be the log-linear link (log) or the logistic link function (logit).
<code>Xlambda_positive</code>	Optional vector of logical indicating which elements of $\lambda_x$ should be constrained to be positive.

regular_type	Regularization method which can be lasso, scad or mcp. See <a href="#">gdina</a> for more information and references.
regular_lam	Numeric. Regularization parameter
regular_w	Vector for weighting the regularization penalty
regular_n	Vector of regularization factor. This will be typically the sample size.
maxiter	Maximum number of iterations
conv	Convergence criterion for item parameters and distribution parameters
globconv	Global deviance convergence criterion
msteps	Maximum number of M steps in estimating $b$ and $a$ item parameters. The default is to use 4 M steps.
convM	Convergence criterion in M step
decrease.increments	Should in the M step the increments of $a$ and $b$ parameters decrease during iterations? The default is FALSE. If there is an increase in deviance during estimation, setting decrease.increments to TRUE is recommended.
oldfac	Factor $f$ between 0 and 1 to control convergence behavior. If $x_t$ denotes the estimated parameter in iteration $t$ , then the regularized estimate $x_t^*$ is obtained by $x_t^* = f x_{t-1} + (1-f)x_t$ . Therefore, values of oldfac near to one only allow for small changes in estimated parameters from in succeeding iterations.
dampening_factor	Factor larger than one defining the specified decrease in decrements in iterations.
seed	Simulation seed for initial parameters. The default of NULL corresponds to a random seed.
progress	An optional logical indicating whether the function should print the progress of iteration in the estimation process.
PEM	Logical indicating whether the P-EM acceleration should be applied (Berlinet & Roland, 2012).
PEM_itermax	Number of iterations in which the P-EM method should be applied.
object	A required object of class slca
file	Optional file name for a file in which summary should be sinked.
x	A required object of class slca
...	Optional parameters to be passed to or from other methods will be ignored.

## Details

The structured latent class model allows for general constraints of items  $i$  in categories  $h$  and classes  $j$ . The item response model is

$$P(X_i = h|j) = \frac{\exp(x_{ihj})}{\sum_l \exp(x_{ilj})}$$

with linear constraints on the class specific probabilities

$$x_{ihj} = \sum_v q_{ihjv} \lambda_{xv}$$

Linear restrictions on the  $\lambda_x$  parameter can be specified by a matrix equation  $V_x \lambda_x = c_x$  (see `Xlambda.constr.v` and `Xlambda.constr.c`; Neuhaus, 1996).

The latent class distribution can be smoothed by a log-linear link function (Xu & von Davier, 2008) or a logistic link function (Formann, 1992). For class  $j$  in group  $g$  employing a link function  $h$ , it holds that

$$h[P(j|g)] \propto \sum_w r_{jw} \delta_{gw}$$

where group-specific distributions are allowed. The values  $r_{jw}$  are specified in the design matrix `delta.designmatrix`.

This model contains classical uni- and multidimensional latent trait models, latent class analysis, located latent class analysis, cognitive diagnostic models, the general diagnostic model and mixture item response models as special cases (see Formann & Kohlmann, 1998; Formann, 2007).

The function also allows for regularization of  $\lambda_{xv}$  parameters using the lasso approach (Sun et al., 2016). More formally, the penalty function can be written as

$$pen(\lambda_x) = p_\lambda \sum_v n_v w_v |\lambda_{xv}|$$

where  $p_\lambda$  can be specified with `regular_lam`,  $w_v$  can be specified with `regular_w`, and  $n_v$  can be specified with `regular_n`.

## Value

An object of class `slca`. The list contains the following entries:

<code>item</code>	Data frame with conditional item probabilities
<code>deviance</code>	Deviance
<code>ic</code>	Information criteria, number of estimated parameters
<code>Xlambda</code>	Estimated $\lambda_x$ parameters
<code>se.Xlambda</code>	Standard error of $\lambda_x$ parameters
<code>pi.k</code>	Trait distribution
<code>pjk</code>	Item response probabilities evaluated for all classes
<code>n.ik</code>	An array of expected counts $n_{cikg}$ of ability class $c$ at item $i$ at category $k$ in group $g$
<code>G</code>	Number of groups
<code>I</code>	Number of items
<code>N</code>	Number of persons
<code>delta</code>	Parameter estimates for skillspace representation
<code>covdelta</code>	Covariance matrix of parameter estimates for skillspace representation
<code>MLE.class</code>	Classified skills for each student (MLE)
<code>MAP.class</code>	Classified skills for each student (MAP)
<code>data</code>	Original data frame
<code>group.stat</code>	Group statistics (sample sizes, group labels)

p.xi.aj	Individual likelihood
posterior	Individual posterior distribution
K.item	Maximal category per item
time	Info about computation time
skillspace	Used skillspace parametrization
iter	Number of iterations
seed.used	Used simulation seed
Xlambda.init	Used initial lambda parameters
delta.init	Used initial delta parameters
converged	Logical indicating whether convergence was achieved.

### Note

If some items have differing number of categories, appropriate class probabilities in non-existing categories per items can be practically set to zero by loading an item for all skill classes on a fixed  $\lambda_x$  parameter of a small number, e.g. -999.

The implementation of the model builds on pieces work of Anton Formann. See <http://www.antonformann.at/> for more information.

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## See Also

For latent trait models with continuous latent variables see the **mirt** or **TAM** packages. For a discrete trait distribution see the **MultiLCIRT** package.

For latent class models see the **poLCA**, **covLCA** or **randomLCA** package.

For mixture Rasch or mixture IRT models see the **psychomix** or **mRm** package.

## Examples

```
#####
# EXAMPLE 1: data.Students | (Generalized) Partial Credit Model
#####

data(data.Students, package="CDM")

dat <- data.Students[, c("mj1","mj2","mj3","mj4","sc1", "sc2") ]
# define discretized ability
theta.k <- seq( -6, 6, len=21 )

###* Model 1: Partial credit model

# define design matrix for lambda
I <- ncol(dat)
maxK <- 4
TP <- length(theta.k)
NXlam <- I*(maxK-1) + 1      # number of estimated parameters
      # last parameter is joint slope parameter
Xdes <- array( 0, dim=c(I, maxK, TP, NXlam ) )
# Item1Cat1, ..., Item1Cat3, Item2Cat1, ...,
dimnames(Xdes)[[1]] <- colnames(dat)
dimnames(Xdes)[[2]] <- paste0("Cat", 1:(maxK) )
dimnames(Xdes)[[3]] <- paste0("Class", 1:TP )
v2 <- unlist( sapply( 1:I, FUN=function(ii){ # ii
  paste0( paste0( colnames(dat)[ii], "_b" ), "Cat", 1:(maxK-1) )
}, simplify=FALSE) )
dimnames(Xdes)[[4]] <- c( v2, "a" )
# define theta design and item discriminations
for (ii in 1:I){
  for (hh in 1:(maxK-1) ){
    Xdes[ii, hh + 1,, NXlam ] <- hh * theta.k
  }
}
# item intercepts
for (ii in 1:I){
  for (hh in 1:(maxK-1) ){
    # ii <- 1 # Item # hh <- 1 # category
    Xdes[ii,hh+1,, ( ii - 1)*(maxK-1) + hh] <- 1
  }
}
#####
# skill space designmatrix
TP <- length(theta.k)
```

```

w1 <- stats::dnorm(theta.k)
w1 <- w1 / sum(w1)
delta.designmatrix <- matrix( 1, nrow=TP, ncol=1 )
delta.designmatrix[,1] <- log(w1)

# initial lambda parameters
Xlambda.init <- c( stats::rnorm( dim(Xdes)[[4]] - 1 ), 1 )
# fixed delta parameter
delta.fixed <- cbind( 1, 1,1 )

# estimate model
mod1 <- CDM::slca( dat, Xdes=Xdes, delta.designmatrix=delta.designmatrix,
                  Xlambda.init=Xlambda.init, delta.fixed=delta.fixed )
summary(mod1)
plot(mod1, cex.names=.7 )

## Not run:
### Model 2: Partial credit model with some parameter constraints
# fixed lambda parameters
Xlambda.fixed <- cbind( c(1,19), c(3.2,1.52 ) )
# 1st parameter=3.2
# 19th parameter=1.52 (joint item slope)
mod2 <- CDM::slca( dat, Xdes=Xdes, delta.designmatrix=delta.designmatrix,
                  delta.init=delta.init, Xlambda.init=Xlambda.init, delta.fixed=delta.fixed,
                  Xlambda.fixed=Xlambda.fixed, maxiter=70 )

### Model 3: Partial credit model with non-normal distribution
Xlambda.fixed <- cbind( c(1,19), c(3.2,1) ) # fix item slope to one
delta.designmatrix <- cbind( 1, theta.k, theta.k^2, theta.k^3 )
mod3 <- CDM::slca( dat, Xdes=Xdes, delta.designmatrix=delta.designmatrix,
                  Xlambda.fixed=Xlambda.fixed, maxiter=200 )
summary(mod3)

# non-normal distribution with convergence regularizing factor oldfac
mod3a <- CDM::slca( dat, Xdes=Xdes, delta.designmatrix=delta.designmatrix,
                  Xlambda.fixed=Xlambda.fixed, maxiter=500, oldfac=.95 )
summary(mod3a)

### Model 4: Generalized Partial Credit Model

# estimate generalized partial credit model without restrictions on trait
# distribution and item parameters to ensure better convergence behavior
# Note that two parameters are not identifiable and information criteria
# have to be adapted.

#---
# define design matrix for lambda
I <- ncol(dat)
maxK <- 4
TP <- length(theta.k)
NXlam <- I*(maxK-1) + I # number of estimated parameters
Xdes <- array( 0, dim=c(I, maxK, TP, NXlam ) )
# Item1Cat1, ..., Item1Cat3, Item2Cat1, ...,

```

```

dimnames(Xdes)[[1]] <- colnames(dat)
dimnames(Xdes)[[2]] <- paste0("Cat", 1:(maxK) )
dimnames(Xdes)[[3]] <- paste0("Class", 1:TP )
v2 <- unlist( sapply( 1:I, FUN=function(ii){ # ii
  paste0( paste0( colnames(dat)[ii], "_b" ), "Cat", 1:(maxK-1) )
}, simplify=FALSE) )
dimnames(Xdes)[[4]] <- c( v2, paste0( colnames(dat),"_a" ) )
dimnames(Xdes)
# define theta design and item discriminations
for (ii in 1:I){
  for (hh in 1:(maxK-1) ){
    Xdes[ii, hh + 1,, I*(maxK-1) + ii ] <- hh * theta.k
  }
}
# item intercepts
for (ii in 1:I){
  for (hh in 1:(maxK-1) ){
    Xdes[ii,hh+1,, ( ii - 1)*(maxK-1) + hh] <- 1
  }
}
#****
# skill space designmatrix
delta.designmatrix <- cbind( 1, theta.k,theta.k^2 )
# initial lambda parameters from partial credit model
Xlambda.init <- mod1$Xlambda
Xlambda.init <- c( mod1$Xlambda[ - length(Xlambda.init) ],
  rep( Xlambda.init[ length(Xlambda.init) ],I) )

# estimate model
mod4 <- CDM::slca( dat, Xdes=Xdes, Xlambda.init=Xlambda.init,
  delta.designmatrix=delta.designmatrix, decrease.increments=TRUE,
  maxiter=300 )

#####
# EXAMPLE 2: Latent class model with two classes
#####

set.seed(9876)
I <- 7 # number of items
# simulate response probabilities
a1 <- stats::runif(I, 0, .4 )
a2 <- stats::runif(I, .6, 1 )
N <- 1000 # sample size
# simulate data in two classes of proportions .3 and .7
N1 <- round(.3*N)
dat1 <- 1 * ( matrix(a1,N1,I,byrow=TRUE) > matrix( stats::runif( N1 * I), N1, I ) )
N2 <- round(.7*N)
dat2 <- 1 * ( matrix(a2,N2,I,byrow=TRUE) > matrix( stats::runif( N2 * I), N2, I ) )
dat <- rbind( dat1, dat2 )
colnames(dat) <- paste0("I", 1:I)

# define design matrices
TP <- 2 # two classes

```

```

# The idea is that latent classes refer to two different "dimensions".
# Items load on latent class indicators 1 and 2, see below.
Xdes <- array(0, dim=c(I,2,2,2*I) )
items <- colnames(dat)
dimnames(Xdes)[[4]] <- c(paste0( colnames(dat), "Class", 1),
                        paste0( colnames(dat), "Class", 2) )
  # items, categories, classes, parameters
# probabilities for correct solution
for (ii in 1:I){
  Xdes[ ii, 2, 1, ii ] <- 1 # probabilities class 1
  Xdes[ ii, 2, 2, ii+I ] <- 1 # probabilities class 2
}
# estimate model
mod1 <- CDM::slca( dat, Xdes=Xdes )
summary(mod1)

#####
# EXAMPLE 3: Mixed Rasch model with two classes
#####

set.seed(987)
library(sirt)
# simulate two latent classes of Rasch populations
I <- 15 # 6 items
b1 <- seq( -1.5, 1.5, len=I) # difficulties latent class 1
b2 <- b1 # difficulties latent class 2
b2[ c(4,7, 9, 11, 12, 13) ] <- c(1, -.5, -.5, .33, .33, -.66 )
N <- 3000 # number of persons
wgt <- .25 # class probability for class 1
# class 1
dat1 <- sirt::sim.raschtype( stats::rnorm( wgt*N ), b1 )
# class 2
dat2 <- sirt::sim.raschtype( stats::rnorm( (1-wgt)*N, mean=1, sd=1.7), b2 )
dat <- rbind( dat1, dat2 )
# theta grid
theta.k <- seq( -5, 5, len=9 )
TP <- length(theta.k)

*** Model 1: Rasch model with normal distribution
maxK <- 2
NXlam <- I + 1
Xdes <- array( 0, dim=c(I, maxK, TP, NXlam) )
dimnames(Xdes)[[1]] <- colnames(dat)
dimnames(Xdes)[[2]] <- paste0("Cat", 1:(maxK) )
dimnames(Xdes)[[4]] <- c( paste0( "b_", colnames(dat)[1:I] ), "a" )
# define item difficulties
for (ii in 1:I){
  Xdes[ii, 2,, ii ] <- -1
}
# theta design
for (tt in 1:TP){
  Xdes[1:I, 2, tt, I + 1] <- theta.k[tt]
}

```



```

# skill space definition
delta.designmatrix <- cbind( 1, theta.k^2 )
delta.fixed <- NULL
Xlambda.init <- c( stats::runif( I, -.8, .8 ), 1 )
Xlambda.fixed <- cbind( I+1, 1 )
# estimate model
mod1 <- CDM::slca( dat, Xdes=Xdes, delta.designmatrix=delta.designmatrix,
                  delta.fixed=delta.fixed, Xlambda.fixed=Xlambda.fixed,
                  Xlambda.init=Xlambda.init, decrease.increments=TRUE, maxiter=200 )
summary(mod1)

**** Model 1b: Constraint the sum of item difficulties to zero

# change skill space definition
delta.designmatrix <- cbind( 1, theta.k, theta.k^2 )
delta.fixed <- NULL
# constrain sum of difficulties Xlambda parameters to zero
Xlambda.constr.V <- matrix( 1, nrow=I+1, ncol=1 )
Xlambda.constr.V[I+1,1] <- 0
Xlambda.constr.c <- c(0)
# estimate model
mod1b <- CDM::slca( dat, Xdes=Xdes, delta.designmatrix=delta.designmatrix,
                   Xlambda.fixed=Xlambda.fixed, Xlambda.constr.V=Xlambda.constr.V,
                   Xlambda.constr.c=Xlambda.constr.c )
summary(mod1b)

**** Model 2: Mixed Rasch model with two latent classes
NXlam <- 2*I +2
Xdes <- array( 0, dim=c(I, maxK, 2*TP, NXlam ) )
dimnames(Xdes)[[1]] <- colnames(dat)
dimnames(Xdes)[[2]] <- paste0("Cat", 1:(maxK) )
dimnames(Xdes)[[4]] <- c( paste0( "bClass1_", colnames(dat)[1:I] ),
                        paste0( "bClass2_", colnames(dat)[1:I] ), "aClass1", "aClass2" )
# define item difficulties
for (ii in 1:I){
  Xdes[ii, 2, 1:TP, ii ] <- -1 # first class
  Xdes[ii, 2, TP + 1:TP, I+ii ] <- -1 # second class
}
# theta design
for (tt in 1:TP){
  Xdes[1:I, 2, tt, 2*I+1 ] <- theta.k[tt]
  Xdes[1:I, 2, TP+tt, 2*I+2 ] <- theta.k[tt]
}
# skill space definition
delta.designmatrix <- matrix( 0, nrow=2*TP, ncol=4 )
delta.designmatrix[1:TP,1] <- 1
delta.designmatrix[1:TP,2] <- theta.k^2
delta.designmatrix[TP + 1:TP,3] <- 1
delta.designmatrix[TP+ 1:TP,4] <- theta.k^2
b1 <- stats::qnorm( colMeans(dat) )
Xlambda.init <- c( stats::runif( 2*I, -1.8, 1.8 ), 1,1 )
Xlambda.fixed <- cbind( c(2*I+1, 2*I+2), 1 )

```

```

# estimate model
mod2 <- CDM::slca( dat, Xdes=Xdes, delta.designmatrix=delta.designmatrix,
                  Xlambda.fixed=Xlambda.fixed, decrease.increments=TRUE,
                  Xlambda.init=Xlambda.init, maxiter=1000 )
summary(mod2)
summary(mod1)
# latent class proportions
stats::aggregate( mod2$pi.k, list( rep(1:2, each=TP)), sum )

*** Model 2b: Different parametrization with sum constraint on item difficulties

# skill space definition
delta.designmatrix <- matrix( 0, nrow=2*TP, ncol=6 )
delta.designmatrix[1:TP,1] <- 1
delta.designmatrix[1:TP,2] <- theta.k
delta.designmatrix[1:TP,3] <- theta.k^2
delta.designmatrix[TP+ 1:TP,4] <- 1
delta.designmatrix[TP+ 1:TP,5] <- theta.k
delta.designmatrix[TP+ 1:TP,6] <- theta.k^2
Xlambda.fixed <- cbind( c(2*I+1,2*I+2), c(1,1) )
b1 <- stats::qnorm( colMeans( dat ) )
Xlambda.init <- c( b1, b1 + stats::runif(I, -1, 1 ), 1, 1 )
# constraints on item difficulties
Xlambda.constr.V <- matrix( 0, nrow=NXlam, ncol=2)
Xlambda.constr.V[1:I, 1 ] <- 1
Xlambda.constr.V[I + 1:I, 2 ] <- 1
Xlambda.constr.c <- c(0,0)
# estimate model
mod2b <- CDM::slca( dat, Xdes=Xdes, delta.designmatrix=delta.designmatrix,
                   Xlambda.fixed=Xlambda.fixed, Xlambda.init=Xlambda.init,
                   Xlambda.constr.V=Xlambda.constr.V, Xlambda.constr.c=Xlambda.constr.c,
                   decrease.increments=TRUE, maxiter=1000 )
summary(mod2b)
stats::aggregate( mod2b$pi.k, list( rep(1:2, each=TP)), sum )

*** Model 2c: Estimation with mRm package
library(mRm)
mod2c <- mRm::mrm(data.matrix=dat, cl=2)
plot(mod2c)
print(mod2c)

*** Model 2d: Estimation with psychomix package
library(psychomix)
mod2d <- psychomix::raschmix(data=dat, k=2, verbose=TRUE )
summary(mod2d)
plot(mod2d)

#####
# EXAMPLE 4: Located latent class model, Rasch model
#####

set.seed(487)
library(sirt)

```

```

I <- 15 # I items
b1 <- seq( -2, 2, len=I) # item difficulties
N <- 4000 # number of persons
# simulate 4 theta classes
theta0 <- c( -2.5, -1, 0.3, 1.3 ) # skill classes
probs0 <- c( .1, .4, .2, .3 )
TP <- length(theta0)
theta <- theta0[ rep(1:TP, round(probs0*N) ) ]
dat <- sirt::sim.raschtype( theta, b1 )

#### Model 1: Located latent class model with 4 classes
maxK <- 2
NXlam <- I + TP
Xdes <- array( 0, dim=c(I, maxK, TP, NXlam) )
dimnames(Xdes)[[1]] <- colnames(dat)
dimnames(Xdes)[[2]] <- paste0("Cat", 1:(maxK) )
dimnames(Xdes)[[3]] <- paste0("Class", 1:TP )
dimnames(Xdes)[[4]] <- c( paste0( "b_", colnames(dat)[1:I] ), paste0("theta", 1:TP) )
# define item difficulties
for (ii in 1:I){
  Xdes[ii, 2,, ii ] <- -1
}
# theta design
for (tt in 1:TP){
  Xdes[1:I, 2, tt, I + tt] <- 1
}

# skill space definition
delta.designmatrix <- diag(TP)
Xlambda.init <- c( - stats::qnorm( colMeans(dat) ), seq(-2,1,len=TP) )
# constraint on item difficulties
Xlambda.constr.V <- matrix( 0, nrow=NXlam, ncol=1)
Xlambda.constr.V[1:I,1] <- 1
Xlambda.constr.c <- c(0)
delta.init <- matrix( c(1,1,1,1), TP, 1 )
# estimate model
mod1 <- CDM::slca( dat, Xdes=Xdes, delta.designmatrix=delta.designmatrix,
  delta.init=delta.init, Xlambda.init=Xlambda.init,
  Xlambda.constr.V=Xlambda.constr.V, Xlambda.constr.c=Xlambda.constr.c,
  decrease.increments=TRUE, maxiter=400 )
summary(mod1)
# compare estimated and simulated theta class locations
cbind( mod1$Xlambda[ - c(1:I) ], theta0 )
# compare estimated and simulated latent class proportions
cbind( mod1$pi.k, probs0 )

#####
# EXAMPLE 5: DINA model with two skills
#####

set.seed(487)
N <- 3000 # number of persons
# define Q-matrix

```

```

I <- 9 # 9 items
NS <- 2 # 2 skills
TP <- 4 # number of skill classes
Q <- scan( nlines=3)
  1 0  1 0  1 0
  0 1  0 1  0 1
  1 1  1 1  1 1
Q <- matrix(Q, I, ncol=NS,byrow=TRUE)
# define skill distribution
alpha0 <- matrix( c(0,0,1,0,0,1,1,1), nrow=4,ncol=2,byrow=TRUE)
prob0 <- c( .2, .4, .1, .3 )
alpha <- alpha0[ rep( 1:TP, prob0*N),]
# define guessing and slipping parameters
guess <- round( stats::runif(I, 0, .4 ), 2 )
slip <- round( stats::runif(I, 0, .3 ), 2 )
# simulate data according to the DINA model
dat <- CDM::sim.din( q.matrix=Q, alpha=alpha, slip=slip, guess=guess )$dat

# define Xlambda design matrix
maxK <- 2
NXlam <- 2*I
Xdes <- array( 0, dim=c(I, maxK, TP, NXlam ) )
dimnames(Xdes)[[1]] <- colnames(dat)
dimnames(Xdes)[[2]] <- paste0("Cat", 1:(maxK) )
dimnames(Xdes)[[3]] <- c("S00","S10","S01","S11")
dimnames(Xdes)[[4]] <- c( paste0("guess",1:I ), paste0( "antislip", 1:I ) )
dimnames(Xdes)
# define item difficulties
for (ii in 1:I){
  # define latent responses
  latresp <- 1*( alpha0 %*% Q[ii,]==sum(Q[ii,]) )[,1]
  # model slipping parameters
  Xdes[ii, 2, latresp==1, I+ii ] <- 1
  # guessing parameters
  Xdes[ii, 2, latresp==0, ii ] <- 1
}
Xdes[1,2,,]
Xdes[7,2,,]
# skill space definition
delta.designmatrix <- diag(TP)
Xlambda.init <- c( rep( stats::qlogis( .2 ), I ), rep( stats::qlogis( .8 ), I ) )

# estimate DINA model with slca function
mod1 <- CDM::slca( dat, Xdes=Xdes, delta.designmatrix=delta.designmatrix,
                  Xlambda.init=Xlambda.init, decrease.increments=TRUE, maxiter=400 )
summary(mod1)

# compare estimated and simulated latent class proportions
cbind( mod1$pi.k, probs0 )
# compare estimated and simulated guessing parameters
cbind( mod1$pjk[1,,2], guess )
# compare estimated and simulated slipping parameters
cbind( 1 - mod1$pjk[4,,2], slip )

```

```
#####
# EXAMPLE 6: Investigating differential item functioning in Rasch models
#           with regularization
#####

#---- simulate data
set.seed(987)
N <- 1000 # number of persons in a group
I <- 20   # number of items
#* population parameters of two groups
mu1 <- 0
mu2 <- .6
sd1 <- 1.4
sd2 <- 1
# item difficulties
b <- seq(-1.1, 1.1, len=I)
# define some DIF effects
dif <- rep(0,I)
dif[ c(3,6,9,12) ] <- c( .6, -1, .75, -.35 )
print(dif)
#* simulate datasets
dat1 <- sirt::sim.raschtype( rnorm(N, mean=mu1, sd=sd1), b=b - dif / 2 )
colnames(dat1) <- paste0("I", 1:I, "_G1")
dat2 <- sirt::sim.raschtype( rnorm(N, mean=mu2, sd=sd2), b=b + dif / 2 )
colnames(dat2) <- paste0("I", 1:I, "_G2")
dat <- CDM::CDM_rbind_fill( dat1, dat2 )
dat <- data.frame( "group"=rep(1:2, each=N), dat )

#-- nodes for distribution
theta.k <- seq(-4, 4, len=11)
# define design matrix for lambda
nitems <- ncol(dat) - 1
maxK <- 2
TP <- length(theta.k)
NXlam <- 2*I + 1
Xdes <- array( 0, dim=c( nitems, maxK, TP, NXlam ) )
dimnames(Xdes)[[1]] <- colnames(dat)[-1]
dimnames(Xdes)[[2]] <- paste0("Cat", 0:(maxK-1) )
dimnames(Xdes)[[3]] <- paste0("Theta", 1:TP )
dimnames(Xdes)[[4]] <- c( paste0("b", 1:I ), paste0("dif", 1:I ), "const" )
# define theta design
for (ii in 1:nitems){
  Xdes[ii,2,NXlam] <- theta.k
}
# item intercepts and DIF effects
for (ii in 1:I){
  Xdes[c(ii,ii+I),2,, ii] <- -1
  Xdes[ii,2,,ii+I] <- - 1/2
  Xdes[ii+I,2,,ii+I] <- 1/2
}
#--- skill space designmatrix
TP <- length(theta.k)
```

```

w1 <- stats::dnorm(theta.k)
w1 <- w1 / sum(w1)
delta.designmatrix <- matrix( 1, nrow=TP, ncol=2 )
delta.designmatrix[,2] <- log(w1)

# fixed lambda parameters
Xlambda.fixed <- cbind(NXlam, 1 )
# initial Xlambda parameters
dif_sim <- 0*stats::rnorm(I, sd=.2)
Xlambda.init <- c( - stats::qnorm( colMeans(dat1) ), dif_sim, 1 )

# delta.fixed
delta.fixed <- cbind( 1, 1, 0 )
# regularization parameter
regular_lam <- .2
# weighting vector: regularize only DIF effects
regular_w <- c( rep(0,I), rep(1,I), 0 )

#--- estimation model with scad penalty
mod1 <- CDM::slca( dat[, -1], group=dat$group, Xdes=Xdes,
                 delta.designmatrix=delta.designmatrix, regular_type="scad",
                 Xlambda.init=Xlambda.init, delta.fixed=delta.fixed, Xlambda.fixed=Xlambda.fixed,
                 regular_lam=regular_lam, regular_w=regular_w )
# compare true and estimated DIF effects
cbind( "true"=dif, "estimated"=round(coef(mod1)[seq(I+1,2*I)],2) )
summary(mod1)

## End(Not run)

```

---

summary.din

*Summary Method for Objects of Class din*


---

## Description

S3 method to summarize objects of the class `din`.

## Usage

```

## S3 method for class 'din'
summary(object, top.n.skill.classes=6, overwrite=FALSE, ...)

```

## Arguments

<code>object</code>	A required object of class <code>din</code> , obtained from a call to the function <code>din</code> .
<code>top.n.skill.classes</code>	A numeric, specifying the number of skill classes, starting with the most frequent, to be returned. Default value is 6.
<code>overwrite</code>	An optional boolean, specifying whether or not the method is supposed to overwrite an existing log file. If the log file exists and <code>overwrite</code> is <code>FALSE</code> , the user is asked to confirm the overwriting.

... Optional parameters to be passed to or from other methods will be ignored.

### Details

The function `summary.din` returns an object of the class `summary.din` (see ‘Value’), for which a print method, `print.summary.din`, is provided. Specific summary information details such as individual item parameters and their discrimination indices can be accessed through assignment (see ‘Examples’).

### Value

If the argument object is of required type, `summary.din` returns a named list, of the class `summary.din`, consisting of the following seven components:

CALL	A character specifying the model rule, the number of items and the number of attributes underlying the items.
IDI	A matrix giving the item discrimination index (IDI; Lee, de la Torre & Park, 2012) for each item $j$ $IDI_j = 1 - s_j - g_j,$ <p>where a high IDI corresponds to favorable test items which have both low guessing and slipping rates.</p>
SKILL.CLASSES	A vector giving the <code>top.n.skill.classes</code> most frequent skill classes and the corresponding class probability.
AIC	A numeric giving the AIC of the specified model object.
BIC	A numeric giving the BIC of the specified model object.
log.file	A character giving the path and file of a specified log file.
din.object	The object of class <code>din</code> for which the summary was requested.

### References

- Lee, Y.-S., de la Torre, J., & Park, Y. S. (2012). Relationships between cognitive diagnosis, CTT, and IRT indices: An empirical investigation. *Asia Pacific Educational Research*, *13*, 333-345.
- Rupp, A. A., Templin, J. L., & Henson, R. A. (2010) *Diagnostic Measurement: Theory, Methods, and Applications*. New York: The Guilford Press.

### See Also

`plot.din`, the S3 method for plotting objects of the class `din`; `print.din`, the S3 method for printing objects of the class `din`; `summary.din`, the S3 method for summarizing objects of the class `din`, which creates objects of the class `summary.din`; `din`, the main function for DINA and DINO parameter estimation, which creates objects of the class `din`. See also [CDM-package](#) for general information about this package.

## Examples

```
##
## (1) examples based on dataset fractions.subtraction.data
##

## Parameter estimation of DINA model
# rule="DINA" is default
fractions.dina <- CDM::din(data=CDM::fraction.subtraction.data,
                          q.matrix=CDM::fraction.subtraction.qmatrix, rule="DINA")

## corresponding summaries, including diagnostic accuracies,
## most frequent skill classes and information
## criteria AIC and BIC
summary(fractions.dina)

## In particular, accessing detailed summary through assignment
detailed.summary.fs <- summary(fractions.dina)
str(detailed.summary.fs)
```

---

summary\_sink

*Prints summary and sink Output in a File*

---

## Description

Prints summary and sink output in a File

## Usage

```
summary_sink( object, file, append=FALSE, ...)
```

## Arguments

object	Object for which a summary method is defined
file	File name
append	Optional logical indicating whether console output should be appended to an already existing file. See argument append in <a href="#">base::sink</a> .
...	Further arguments passed to summary.

## See Also

[base::sink](#), [base::summary](#)



## Examples

```
## Not run:
#####
# EXAMPLE 1: summary_sink example for lm function
#####

#--- simulate some data
set.seed(997)
N <- 200
x <- stats::rnorm( N )
y <- .4 * x + stats::rnorm(N, sd=.5 )

#--- fit a linear model and sink summary into a file
mod1 <- stats::lm( y ~ x )
CDM::summary_sink(mod1, file="my_model")

#--- fit a second model and append it to file
mod2 <- stats::lm( y ~ x + I(x^2) )
CDM::summary_sink(mod2, file="my_model", append=TRUE )

## End(Not run)
```

vcov

*Asymptotic Covariance Matrix, Standard Errors and Confidence Intervals*

## Description

Computes the asymptotic covariance matrix for `din` objects. The covariance matrix is computed using the empirical cross-product approach (see Paek & Cai, 2014).

In addition, an S3 method `IRT.se` is defined which produces an extended output including `vcov` and `confint`.

## Usage

```
## S3 method for class 'din'
vcov(object, extended=FALSE, infomat=FALSE, ind.item.skillprobs=TRUE,
      ind.item=FALSE, diagcov=FALSE, h=.001,...)

## S3 method for class 'din'
confint(object, parm, level=.95, extended=FALSE,
        ind.item.skillprobs=TRUE, ind.item=FALSE, diagcov=FALSE, h=.001, ... )

IRT.se(object, ... )

## S3 method for class 'din'
IRT.se( object, extended=FALSE, parm=NULL, level=.95,
        infomat=FALSE, ind.item.skillprobs=TRUE, ind.item=FALSE,
        diagcov=FALSE, h=.001, ... )
```

**Arguments**

<code>object</code>	An object inheriting from class <code>din</code> .
<code>extended</code>	An optional logical indicating whether the covariance matrix should be calculated for an extended set of parameters (estimated and derived parameters).
<code>infomat</code>	An optional logical indicating whether the information matrix instead of the covariance matrix should be the output.
<code>ind.item.skillprobs</code>	Optional logical indicating whether the covariance between item parameters and skill class probabilities are assumed to be zero.
<code>ind.item</code>	Optional logical indicating whether covariances of item parameters between different items are zero.
<code>diagcov</code>	Optional logical indicating whether all covariances between estimated parameters are set to zero.
<code>h</code>	Parameter used for numerical differentiation for computing the derivative of the log-likelihood function.
<code>parm</code>	Vector of parameters. If it is missing, then for all estimated parameters a confidence interval is calculated.
<code>level</code>	Confidence level
<code>...</code>	Additional arguments to be passed.

**Value**

`coef`: A vector of parameters.

`vcov`: A covariance matrix. The corresponding coefficients can be extracted as the attribute `coef` from this object.

`IRT.se`: A data frame containing coefficients, standard errors and confidence intervals for all parameters.

**References**

Paek, I., & Cai, L. (2014). A comparison of item parameter standard error estimation procedures for unidimensional and multidimensional item response theory modeling. *Educational and Psychological Measurement*, 74(1), 58-76.

**See Also**

[din](#), [coef.din](#)

**Examples**

```
## Not run:
#####
# EXAMPLE 1: DINA model sim.dina
#####

data(sim.dina, package="CDM")
```

```

data(sim.qmatrix, package="CDM")

dat <- sim.dina
q.matrix <- sim.qmatrix

##### Model 1: DINA Model
mod1 <- CDM::din( dat, q.matrix=q.matrix, rule="DINA")
# look into parameter table of the model
mod1$partable
# covariance matrix
covmat1 <- vcov(mod1 )
# extract coefficients
coef(mod1)
# extract standard errors
sqrt( diag( covmat1))
# compute confidence intervals
confint( mod1, level=.90 )
# output table with standard errors
IRT.se( mod1, extended=TRUE )

##### Model 2: Constrained DINA Model

# fix some slipping parameters
constraint.slip <- cbind( c(2,3,5), c(.15,.20,.25) )
# set some skill class probabilities to zero
zeroprob.skillclasses <- c(2,4)
# estimate model
mod2 <- CDM::din( dat, q.matrix=q.matrix, guess.equal=TRUE,
  constraint.slip=constraint.slip, zeroprob.skillclasses=zeroprob.skillclasses)
# parameter table
mod2$partable
# freely estimated coefficients
coef(mod2)
# covariance matrix (estimated parameters)
vmod2a <- vcov(mod2)
sqrt( diag( vmod2a))          # standard errors
colnames( vmod2a )
names( attr( vmod2a, "coef" ) ) # extract coefficients

# covariance matrix (more parameters, extended=TRUE)
vmod2b <- vcov(mod2, extended=TRUE)
sqrt( diag( vmod2b))
attr( vmod2b, "coef")
# attach standard errors to parameter table
partable2 <- mod2$partable
partable2 <- partable2[ ! duplicated( partable2$parnames ), ]
partable2 <- data.frame( partable2, "se"=sqrt( diag( vmod2b)) )
partable2

# confidence interval for parameter "skill1" which is not in the model
# cannot be calculated!
confint(mod2, parm=c( "skill1", "all_guess" ) )
# confidence interval for only some parameters

```

```

confint(mod2, parm=paste0("prob_skill", 1:3 ) )

# compute only information matrix
infomod2 <- vcov(mod2, infomat=TRUE)

## End(Not run)

```

---

WaldTest

*Wald Test for a Linear Hypothesis*


---

### Description

Computes a Wald Test for a parameter  $\theta$  with respect to a linear hypothesis  $R\theta = c$ .

### Usage

```
WaldTest( delta, vcov, R, nobs, cvec=NULL, eps=1E-10 )
```

### Arguments

delta	Estimated parameter
vcov	Estimated covariance matrix
R	Hypothesis matrix
nobs	Number of observations
cvec	Hypothesis vector
eps	Numerical value is added as ridge parameter of the covariance matrix

### Value

A vector containing the  $\chi^2$  statistic (X2), degrees of freedom (df), p value (p) and RMSEA statistic (RMSEA).

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