

# Package ‘pks’

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**Imports** graphics

**Suggests** relations, Rgraphviz

**Description** Fitting and testing probabilistic knowledge structures, especially the basic local independence model (BLIM, Doignon & Flamagne, 1999) and the simple learning model (SLM), using the minimum discrepancy maximum likelihood (MDML) method (Heller & Wickelmaier, 2013 <[doi:10.1016/j.endm.2013.05.145](https://doi.org/10.1016/j.endm.2013.05.145)>).

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blim	<i>Basic Local Independence Models (BLIMs)</i>
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## Description

Fits a basic local independence model (BLIM) for probabilistic knowledge structures by minimum discrepancy maximum likelihood estimation.

## Usage

```
blim(K, N.R, method = c("MD", "ML", "MDML"), R = as.binmat(N.R),
     P.K = rep(1/nstates, nstates),
     beta = rep(0.1, nitems), eta = rep(0.1, nitems),
     betafix = rep(NA, nitems), etafix = rep(NA, nitems),
     betaequal = NULL, etaequal = NULL,
     randinit = FALSE, incradius = 0,
     tol = 1e-07, maxiter = 10000, zeropad = 16)
```

```
blimMD(K, N.R, R = as.binmat(N.R),
       betafix = rep(NA, nitems), etafix = rep(NA, nitems),
       incrule = c("minimum", "hypblc1", "hypblc2"), m = 1)
```

```
## S3 method for class 'blim'
anova(object, ..., test = c("Chisq", "none"))
```

## Arguments

K	a state-by-problem indicator matrix representing the knowledge structure. An element is one if the problem is contained in the state, and else zero.
N.R	a (named) vector of absolute frequencies of response patterns.

method	MD for minimum discrepancy estimation, ML for maximum likelihood estimation, MDML for minimum discrepancy maximum likelihood estimation.
R	a person-by-problem indicator matrix of unique response patterns. Per default inferred from the names of N.R.
P.K	the vector of initial parameter values for probabilities of knowledge states.
beta, eta	vectors of initial parameter values for probabilities of a careless error and a lucky guess, respectively.
betafix, etafix	vectors of fixed error and guessing parameter values; NA indicates a free parameter.
betaequal, etaequal	lists of vectors of problem indices; each vector represents an equivalence class: it contains the indices of problems for which the error or guessing parameters are constrained to be equal. (See Examples.)
randinit	logical, if TRUE then initial parameter values are sampled uniformly with constraints. (See Details.)
incradius	include knowledge states of distance from the minimum discrepant states less than or equal to <code>incradius</code> .
tol	tolerance, stopping criterion for iteration.
maxiter	the maximum number of iterations.
zeropad	the maximum number of items for which an incomplete N.R vector is completed and padded with zeros.
incrule	inclusion rule for knowledge states. (See Details.)
m	exponent for hyperbolic inclusion rules.
object	an object of class <code>blim</code> , typically the result of a call to <code>blim</code> .
test	should the p-values of the chi-square distributions be reported?
...	additional arguments passed to other methods.

## Details

See Doignon and Falmagne (1999) for details on the basic local independence model (BLIM) for probabilistic knowledge structures.

Minimum discrepancy (MD) minimizes the number of expected response errors (careless errors or lucky guesses). Maximum likelihood maximizes the likelihood, possibly at the expense of inflating the error and guessing parameters. Minimum discrepancy maximum likelihood (MDML) maximizes the likelihood subject to the constraint of minimum response errors. See Heller and Wickelmaier (2013) for details on the parameter estimation methods.

If `randinit` is TRUE, initial parameter values are sampled uniformly with the constraint  $\beta + \eta < 1$  (Weisstein, 2013) for the error parameters, and with  $\sum(P.K) == 1$  (Rubin, 1981) for the probabilities of knowledge states. Setting `randinit` to TRUE overrides any values given in the `P.K`, `beta`, and `eta` arguments.

The degrees of freedom in the goodness-of-fit test are calculated as number of possible response patterns minus one or number of respondents, whichever is smaller, minus number of parameters.

`blimMD` uses minimum discrepancy estimation only. Apart from the hyperbolic inclusion rules, all of its functionality is also provided by `blim`. It may be removed in the future.

**Value**

An object of class `blim` having the following components:

<code>discrepancy</code>	the mean minimum discrepancy between response patterns and knowledge states.
<code>P.K</code>	the vector of estimated parameter values for probabilities of knowledge states.
<code>beta</code>	the vector of estimated parameter values for probabilities of a careless error.
<code>eta</code>	the vector of estimated parameter values for probabilities of a lucky guess.
<code>disc.tab</code>	the minimum discrepancy distribution.
<code>K</code>	the knowledge structure.
<code>N.R</code>	the vector of frequencies of response patterns.
<code>nitems</code>	the number of items.
<code>nstates</code>	the number of knowledge states.
<code>npatterns</code>	the number of response patterns.
<code>ntotal</code>	the number of respondents.
<code>nerror</code>	the number of response errors.
<code>npar</code>	the number of parameters.
<code>method</code>	the parameter estimation method.
<code>iter</code>	the number of iterations needed.
<code>loglik</code>	the log-likelihood.
<code>fitted.values</code>	the fitted response frequencies.
<code>goodness.of.fit</code>	the goodness of fit statistic including the likelihood ratio fitted vs. saturated model (G2), the degrees of freedom, and the p-value of the corresponding chi-square distribution. (See Details.)

**References**

- Doignon, J.-P., & Falmagne, J.-C. (1999). *Knowledge spaces*. Berlin: Springer.
- Heller, J., & Wickelmaier, F. (2013). Minimum discrepancy estimation in probabilistic knowledge structures. *Electronic Notes in Discrete Mathematics*, **42**, 49–56. doi:10.1016/j.endm.2013.05.145
- Rubin, D.B. (1981). The Bayesian bootstrap. *The Annals of Statistics*, **9**(1), 130–134. doi:10.1214/aos/1176345338
- Weisstein, E.W. (2013, August 29). Triangle point picking. In *MathWorld – A Wolfram Web Resource*. Retrieved from <https://mathworld.wolfram.com/TrianglePointPicking.html>.

**See Also**

[simulate.blim](#), [plot.blim](#), [residuals.blim](#), [logLik.blim](#), [delineate](#), [jacobian](#), [endm](#), [probability](#), [chess](#).

**Examples**

```

data(DoignonFalmagne7)
K <- DoignonFalmagne7$K # knowledge structure
N.R <- DoignonFalmagne7$N.R # frequencies of response patterns

## Fit basic local independence model (BLIM) by different methods
blim(K, N.R, method = "MD") # minimum discrepancy estimation
blim(K, N.R, method = "ML") # maximum likelihood estimation by EM
blim(K, N.R, method = "MDML") # MDML estimation

## Parameter restrictions: beta_a = beta_b = beta_d, beta_c = beta_e
##                               eta_a = eta_b = 0.1
m1 <- blim(K, N.R, method = "ML",
           betaequal = list(c(1, 2, 4), c(3, 5)),
           etafix = c(0.1, 0.1, NA, NA, NA))
m2 <- blim(K, N.R, method = "ML")
anova(m1, m2)

## See ?endm, ?probability, and ?chess for further examples.

```

---

blimit

*Basic Local Independence Model Identification Analysis*


---

**Description**

Tests the local identifiability of a basic local independence model (BLIM).

**Usage**

```
blimit(K, beta = NULL, eta = NULL, pi = NULL, file_name = NULL)
```

**Arguments**

K	a state-by-problem indicator matrix representing the knowledge structure. An element is one if the problem is contained in the state, and else zero.
beta, eta, pi	vectors of parameter values for probabilities of careless errors, lucky guesses, and knowledge states, respectively.
file_name	name of an output file.

**Details**

See Stefanutti et al. (2012) for details.

The `blimit` function has been adapted from code provided by Andrea Brancaccio, Debora de Chiusole, and Luca Stefanutti. It contains a function to compute the reduced row echelon form based on an implementation in the `pracma` package.

**Value**

A list having the following components:

NItems	the number of items.
NStates	the number of knowledge states.
NPar	the number of parameters.
Rank	the rank of the Jacobian matrix.
NSD	the null space dimension.
RankBeta, RankEta, RankPi, RankBetaEta, RankBetaPi, RankEtaPi	the rank of submatrices of the Jacobian.
DiagBetaEta, DiagBetaPi, DiagEtaPi, DiagBetaEtaPi	diagnostic information about specific parameter trade-offs.
Jacobian	the Jacobian matrix.
beta, eta, pi	the parameter values used in the analysis.

**References**

Stefanutti, L., Heller, J., Anselmi, P., & Robusto, E. (2012). Assessing the local identifiability of probabilistic knowledge structures. *Behavior Research Methods*, **44**(4), 1197–1211. doi:10.3758/s134280120187z

**See Also**

[blim](#), [jacobian](#).

**Examples**

```
K <- as.binmat(c("0000", "1000", "0100", "1110", "1101", "1111"))
set.seed(1234)
info <- blimit(K)
```

---

chess

*Responses to Chess Problems and Knowledge Structures*

---

**Description**

Held, Schrepp and Fries (1995) derive several knowledge structures for the representation of 92 responses to 16 chess problems. See Schrepp, Held and Albert (1999) for a detailed description of these problems.

**Usage**

```
data(chess)
```

## Format

A list consisting of five components:

dst1 a state-by-problem indicator matrix representing the knowledge structure DST1.

dst3 the knowledge structure DST3.

dst4 the knowledge structure DST4.

N.R a named integer vector. The names denote response patterns, the values denote their frequencies.

R a person-by-problem indicator matrix representing the responses. Column names hdbgXX and grazYY identify responses collected in Heidelberg and Graz, respectively.

## Note

The graphs of the precedence relations for DST1 and DST4 in Held et. al (1995) contain mistakes that have been corrected. See examples.

## Source

Held, T., Schrepp, M., & Fries, S. (1995). Methoden zur Bestimmung von Wissensstrukturen – eine Vergleichsstudie. *Zeitschrift fuer Experimentelle Psychologie*, **42**(2), 205–236.

## References

Schrepp, M., Held, T., & Albert, D. (1999). Component-based construction of surmise relations for chess problems. In D. Albert & J. Lukas (Eds.), *Knowledge spaces: Theories, empirical research, and applications* (pp. 41–66). Mahwah, NJ: Erlbaum.

## Examples

```
data(chess)
chess$dst1 # knowledge structure DST1

## Precedence relation (Held et al., 1995, p. 215) and knowledge space
P <- as.binmat(c("1111011101111001", # s
                # "0100000000000000", # gs mistake in Abb. 3
                "0111010100111000", # gs correction
                "0011010000011000", # egs
                "0011010000011000", # eegs
                "0000110000000000", # cs
                "0000010000000000", # gcs
                "0011011100111000", # ts
                "0011010100011000", # ges
                "1111111111111111", # f
                "0111010101111000", # gf
                "0011010000111000", # ggf
                "0000000000010000", # ggff
                "0000000000010000", # ggf
                "011101110111101", # ff
                "011101110111011", # tf
                "0011010100111001"), # tff
```

```

      as.logical = TRUE)
dimnames(P) <- list("<" = colnames(chess$R), ">" = colnames(chess$R))
K <- rbind(∅L, binary_closure(t(P)))
identical(sort(as.pattern(K)),
          sort(as.pattern(chess$dst1)))

blim(chess$dst1, chess$N.R) # Tab. 1

```

---

conversion

*Conversion between Representations of Responses or States*


---

### Description

Converts between binary matrix and pattern representations of response patterns or knowledge states.

### Usage

```

as.pattern(R, freq = FALSE, useNames = FALSE, as.set = FALSE,
          sep = "", emptyset = "{}", as.letters = NULL)

as.binmat(N.R, uniq = TRUE, col.names = NULL, as.logical = FALSE)

is.subset(R)

```

### Arguments

R	an indicator matrix of response patterns or knowledge states.
N.R	either a (named) vector of absolute frequencies of response patterns; or a character vector of response patterns or knowledge states; or a set of sets representing the knowledge structure.
freq	logical, should the frequencies of response patterns be reported?
uniq	logical, if TRUE, only the unique response patterns are returned.
useNames	logical, return response patterns as combinations of item names.
as.set	logical, return response patterns as set of sets.
sep	character to separate the item names.
emptyset	string representing the empty set if useNames is TRUE.
as.letters	deprecated, use useNames instead.
col.names	column names for the state or response matrix.
as.logical	logical, return logical matrix of states.

### Value

as.pattern returns a vector of integers named by the response patterns if freq is TRUE, else a character vector. If as.set is TRUE, the return value is of class set.

as.binmat returns an indicator matrix. If as.logical is TRUE, it returns a logical matrix.

is.subset returns a logical incidence matrix of the subset relation among states.



**See Also**

[blim](#), set in package sets.

**Examples**

```
data(DoignonFalmagne7)
K <- DoignonFalmagne7$K
as.pattern(K, freq = TRUE)
as.pattern(K)
as.pattern(K, useNames = TRUE)
as.pattern(K, as.set = TRUE)

N.R <- DoignonFalmagne7$N.R
dim(as.binmat(N.R))
dim(as.binmat(N.R, uniq = FALSE))

## Knowledge structure as binary matrix
as.binmat(c("000", "100", "101", "111"))
as.binmat(set(set(), set("a"), set("a", "c"), set("a", "b", "c")))
as.binmat(c("000", "100", "101", "111"), as.logical = TRUE)

## Subset relation incidence matrix
is.subset(K)

## Plotting the knowledge structure
if(requireNamespace("relations") &&
  requireNamespace("Rgraphviz")) {
  rownames(K) <- as.pattern(K, useNames = TRUE)
  plot(relations::as.relation(is.subset(K)), main = "")
}
```

---

delineate

*Delineate a Knowledge Structure by a Skill Function*


---

**Description**

Computes the knowledge structure delineated by a skill function.

**Usage**

```
delineate(skillfun, itemID = 1)
```

**Arguments**

skillfun	a data frame or a matrix representing the skill function. It consists of an item indicator and a problem-by-skill indicator matrix.
itemID	index of the column in skillfun that holds the item indicator.

**Details**

The skill function  $(Q, S, \mu)$  indicates for each item in  $Q$  which subsets of skills in  $S$  are required to solve the item. Thus,  $\mu(q)$  is a set containing sets of skills. An item may have multiple entries in `skillfun`, each in a separate row identified by the same `itemID`.

See Doignon and Falmagne (1999, Chap. 4).

**Value**

A list of two components:

K	the knowledge structure delineated by the skill function.
classes	a list of equivalence classes of competence states; the members of these classes are mapped onto the same knowledge state by the problem function induced by the skill function $\mu$ .

**References**

Doignon, J.-P., & Falmagne, J.-C. (1999). *Knowledge spaces*. Berlin: Springer.

**See Also**

[blim](#).

**Examples**

```
# Skill function
# mu(e) = {{s, t}, {s, u}}, mu(f) = {{u}}
# mu(g) = {{s}, {t}}, mu(h) = {{t}}
sf <- read.table(header = TRUE, text = "
  item s t u
  e 1 1 0
  e 1 0 1
  f 0 0 1
  g 1 0 0
  g 0 1 0
  h 0 1 0
")
delineate(sf)

## See ?probability for further examples.
```

---

DoignonFalmagne7

*Artificial Responses from Doignon and Falmagne (1999)*

---

**Description**

Fictitious data set from Doignon and Falmagne (1999, chap. 7). Response patterns of 1000 respondents to five problems. Each respondent is assumed to be in one of nine possible states of the knowledge structure K.

**Usage**

```
data(DoignonFalmagne7)
```

**Format**

A list consisting of two components:

**K** a state-by-problem indicator matrix representing the hypothetical knowledge structure. An element is one if the problem is contained in the state, and else zero.

**N.R** a named numeric vector. The names denote response patterns, the values denote their frequencies.

**Source**

Doignon, J.-P., & Falmagne, J.-C. (1999). *Knowledge spaces*. Berlin: Springer.

**Examples**

```
data(DoignonFalmagne7)
DoignonFalmagne7$K # knowledge structure
DoignonFalmagne7$N.R # response patterns
```

---

endm	<i>Responses and Knowledge Structures from Heller and Wickelmaier (2013)</i>
------	--

---

**Description**

Knowledge structures and 200 artificial responses to four problems are used to illustrate parameter estimation in Heller and Wickelmaier (2013).

**Usage**

```
data(endm)
```

**Format**

A list consisting of three components:

**K** a state-by-problem indicator matrix representing the true knowledge structure that underlies the model that generated the data.

**K2** a slightly misspecified knowledge structure.

**N.R** a named numeric vector. The names denote response patterns, the values denote their frequencies.

## Source

Heller, J., & Wickelmaier, F. (2013). Minimum discrepancy estimation in probabilistic knowledge structures. *Electronic Notes in Discrete Mathematics*, **42**, 49–56. doi:10.1016/j.endm.2013.05.145

## Examples

```
data(endm)
endm$K    # true knowledge structure
endm$K2   # misspecified knowledge structure
endm$N.R  # response patterns

## Generate data from BLIM based on K
blim0 <- list(
  P.K = setNames(c(.1, .15, .15, .2, .2, .1, .1), as.pattern(endm$K)),
  beta = rep(.1, 4),
  eta = rep(.1, 4),
  K = endm$K,
  ntotal = 200)
class(blim0) <- "blim"
simulate(blim0)

## Fit BLIM based on K2
blim1 <- blim(endm$K2, endm$N.R, "MD")
```

---

getKFringe

*Outer and Inner Fringes of a Knowledge Structure*

---

## Description

Returns the outer or inner fringe for each state in a knowledge structure.

## Usage

```
getKFringe(K, nstates = nrow(K), nitens = ncol(K), outer = TRUE)
```

## Arguments

K	a state-by-problem indicator matrix representing the knowledge structure. An element is one if the problem is contained in the state, and else zero.
nstates	the number of knowledge states in K.
nitens	the number of items in K.
outer	logical. If TRUE return outer fringe, else return inner fringe.

**Details**

The outer fringe of a knowledge state is the set of all items that can be learned from that state, such that adding an outer-fringe item to the state results in another state in  $K$ ,

$$K^O = \{q \notin K \mid K \cup \{q\} \in \mathcal{K}\}.$$

The inner fringe of a knowledge state is the set of all items that have been learned most recently to reach that state, such that deleting an inner-fringe item from the state results in another state in  $K$ ,

$$K^I = \{q \in K \mid K - \{q\} \in \mathcal{K}\}.$$

**Value**

A state-by-problem indicator matrix representing the outer or inner fringe for each knowledge state in  $K$ .

**See Also**

[slm](#), [simulate.blim](#).

**Examples**

```
data(DoignonFalmagne7)

## Which items can be learned from each state?
getKFringe(DoignonFalmagne7$K)

## Which items in each state have been recently learned?
getKFringe(DoignonFalmagne7$K, outer = FALSE)
```

---

gradedness

*Forward-/Backward-Gradedness and Downgradability of a Knowledge Structure*

---

**Description**

Checks if a knowledge structure is

- forward- or backward-graded in any item;
- downgradable.

**Usage**

```
is.forward.graded(K)
```

```
is.backward.graded(K)
```

```
is.downgradable(K)
```

**Arguments**

**K** a state-by-problem indicator matrix representing the knowledge structure. An element is one if the problem is contained in the state, and else zero. **K** should have non-empty colnames.

**Details**

A knowledge structure  $K$  is forward-graded in item  $q$ , if  $S \cup \{q\}$  is in  $K$  for every state  $S \in K$ . A knowledge structure  $K$  is backward-graded in item  $q$ , if  $S - \{q\}$  is in  $K$  for every state  $S \in K$ . See Spoto, Stefanutti, and Vidotto (2012).

A knowledge structure  $K$  is downgradable, if its inner fringe is empty only for a single state (the empty set). See Doignon and Falmagne (2015).

**Value**

For forward- and backward-gradedness, a named logical vector with as many elements as columns in **K**.

For downgradability, a single logical value.

**References**

Doignon, J.-P., & Falmagne, J.-C. (2015). Knowledge spaces and learning spaces. *arXiv*. doi:10.48550/arXiv.1511.06757

Spoto, A., Stefanutti, L., & Vidotto, G. (2012). On the unidentifiability of a certain class of skill multi map based probabilistic knowledge structures. *Journal of Mathematical Psychology*, **56**(4), 248–255. doi:10.1016/j.jmp.2012.05.001

**See Also**

[blim](#), [jacobian](#), [getKFringe](#).

**Examples**

```
K <- as.binmat(c("0000", "1000", "1100", "1010", "0110", "1110", "1111"))
is.forward.graded(K)           # forward-graded in a
is.backward.graded(K)         # not backward-graded in a
is.downgradable(K)           # not downgradable
all(K[, "a"] | getKFringe(K)[, "a"]) # every K or outer fringe contains a
```

---

 ita

---

*Item Tree Analysis (ITA)*


---

**Description**

Item tree analysis (ITA) on a set of binary responses.

**Usage**

```
ita(R, L = NULL, makeK = FALSE, search = c("local", "global"))
```

**Arguments**

R	a subject-by-problem indicator matrix representing the responses.
L	the threshold of violations acceptable for the precedence relation. If NULL (default), an optimal threshold is searched for.
makeK	should the corresponding knowledge structure be returned?
search	local (default) or global threshold search.

**Details**

ITA seeks to establish a precedence relation among a set of binary items. For each pair of items  $(p, q)$ , it counts how often  $p$  is not solved if  $q$  is solved, which constitutes a violation of the relation. ITA searches for a threshold  $L$  for the maximum number of violations consistent with a (transitive) precedence relation. Its attempts to minimize the total discrepancy between  $R$  and  $K$ .

See van Leeuwe (1974) and Schrepp (1999) for details.

**Value**

An object of class `ita` having the following components:

K	the knowledge structure corresponding to the precedence relation.
discrepancy	the discrepancy between $R$ and $K$ (fit), between $K$ and $R$ (complexity), and their sum (total).
transitiveL	the vector of transitive thresholds.
searchL	either NULL or the method used for threshold search.
L	the selected or requested threshold.
P	the precedence matrix containing the number of violations.
I	the precedence relation as a logical incidence matrix at threshold $L$ .

**References**

- Schrepp, M. (1999). On the empirical construction of implications between bi-valued test items. *Mathematical Social Sciences*, **38**(3), 361–375. doi:[10.1016/S01654896\(99\)000256](https://doi.org/10.1016/S01654896(99)000256)
- Van Leeuwe, J.F. (1974). Item tree analysis. *Nederlands Tijdschrift voor de Psychologie en haar Grensgebieden*, **29**(6), 475–483.

**See Also**

[blim](#).

**Examples**

```

data(chess)

ita(chess$R) # find (locally) optimal threshold L

i <- ita(chess$R, L = 6, makeK = TRUE)
identical(sort(as.pattern(i$K)),
          sort(as.pattern(chess$dst1)))

## Plotting the precedence relation
if(requireNamespace("relations") &&
    requireNamespace("Rgraphviz")) {
  plot(relations::as.relation(i$I))
}

```

---

jacobian

*Jacobian Matrix for Basic Local Independence Model*


---

**Description**

Computes the Jacobian matrix for a basic local independence model (BLIM).

**Usage**

```

jacobian(object, P.K = rep(1/nstates, nstates),
         beta = rep(0.1, nitems), eta = rep(0.1, nitems),
         betafix = rep(NA, nitems), etafix = rep(NA, nitems))

```

**Arguments**

object	an object of class <code>blim</code> , typically the result of a call to <code>blim</code> .
P.K	the vector of parameter values for probabilities of knowledge states.
beta	the vector of parameter values for probabilities of a careless error.
eta	the vector of parameter values for probabilities of a lucky guess.
betafix, etafix	vectors of fixed error and guessing parameter values; NA indicates a free parameter.

**Details**

This is a draft version. It may change in future releases.

**Value**

The Jacobian matrix. The number of rows equals  $2^{(\text{number of items})} - 1$ , the number of columns equals the number of independent parameters in the model.



## References

Heller, J. (2017). Identifiability in probabilistic knowledge structures. *Journal of Mathematical Psychology*, **77**, 46–57. doi:10.1016/j.jmp.2016.07.008

Stefanutti, L., Heller, J., Anselmi, P., & Robusto, E. (2012). Assessing the local identifiability of probabilistic knowledge structures. *Behavior Research Methods*, **44**(4), 1197–1211. doi:10.3758/s134280120187z

## See Also

[blim](#), [simulate.blim](#), [gradedness](#).

## Examples

```
data(endm)
m <- blim(endm$K2, endm$N.R)

## Test of identifiability
J <- jacobian(m)
dim(J)
qr(J)$rank
```

---

plot.blim

*Diagnostic Plot for Basic Local Independence Models*

---

## Description

Plots BLIM residuals against fitted values.

## Usage

```
## S3 method for class 'blim'
plot(x, xlab = "Predicted response probabilities",
      ylab = "Deviance residuals", ...)
```

## Arguments

`x` an object of class `blim`, typically the result of a call to `blim`.  
`xlab`, `ylab`, ... graphical parameters passed to `plot`.

## Details

The deviance residuals are plotted against the predicted response probabilities for each response pattern.

## See Also

[blim](#), [residuals.blim](#).

**Examples**

```
## Compare MD and MDML estimation

data(DoignonFalmagne7)

blim1 <- blim(DoignonFalmagne7$K, DoignonFalmagne7$N.R, method="MD")
blim2 <- blim(DoignonFalmagne7$K, DoignonFalmagne7$N.R, method="MDML")

par(mfrow = 1:2)      # residuals versus fitted values
plot(blim1, main = "MD estimation", ylim = c(-4, 4))
plot(blim2, main = "MDML estimation", ylim = c(-4, 4))
```

---

```
print.blim          Print a blim Object
```

---

**Description**

Prints the output of a blim model object.

**Usage**

```
## S3 method for class 'blim'
print(x, P.Kshow = FALSE, errshow = TRUE,
      digits=max(3, getOption("digits") - 2), ...)
```

**Arguments**

x	an object of class blim, typically the result of a call to <a href="#">blim</a> .
P.Kshow	logical, should the estimated distribution of knowledge states be printed?
errshow	logical, should the estimates of careless error and lucky guess parameters be printed?
digits	a non-null value for digits specifies the minimum number of significant digits to be printed in values.
...	further arguments passed to or from other methods. None are used in this method.

**Value**

Returns the blim object invisibly.

**See Also**

[blim](#).

**Examples**

```
data(DoignonFalmagne7)

blim1 <- blim(DoignonFalmagne7$K, DoignonFalmagne7$N.R)
print(blim1, showP.K = TRUE)
```

**Description**

This data set contains responses to problems in elementary probability theory observed before and after some instructions (the so-called learning object) were given. Data were collected both in the lab and via an online questionnaire. Of the 1127 participants eligible in the online study, 649 were excluded because they did not complete the first set of problems (p101, ..., p112) or they responded too quickly or too slowly. Based on similar criteria, further participants were excluded for the second set of problems, indicated by missing values in the variables b201, ..., b212. Problems were presented in random order.

Participants were randomized to two conditions: an enhanced learning object including instructions with examples and a basic learning object without examples. Instructions were given on four concepts: how to calculate the classic probability of an event (pb), the probability of the complement of an event (cp), of the union of two disjoint events (un), and of two independent events (id).

The questionnaire was organized as follows:

**Page 1** Welcome page.

**Page 2** Demographic data.

**Page 3** First set of problems.

**Page 4 to 8** Instructions (learning object).

**Page 9** Second set of problems.

**Page 10** Feedback about number of correctly solved problems.

**Usage**

```
data(probability)
```

**Format**

A data frame with 504 cases and 68 variables:

- case a factor giving the case id, a five-digits code the first digit denoting lab or online branch of the study, the last four digits being the case number.
- lastpage Which page of the questionnaire was reached before quitting? The questionnaire consisted of ten pages.
- mode a factor; lab or online branch of study.
- started a timestamp of class POSIXlt. When did participant start working on the questionnaire?
- sex a factor coding sex of participant.
- age age of participant.
- educat education as a factor with three levels: 1 secondary school or below; 2 higher education entrance qualification; 3 university degree.

- fos field of study. Factor with eight levels: ecla economics, business, law; else miscellaneous; hipo history, politics; lang languages; mabi mathematics, physics, biology; medi medical science; phth philosophy, theology; psco psychology, computer science, cognitive science.
- semester ordered factor. What semester are you in?
- learnobj a factor with two levels: enhan learning object enhanced with examples; basic learning object without examples.

The twelve problems of the first part (before the learning object):

- p101 A box contains 30 marbles in the following colors: 8 red, 10 black, 12 yellow. What is the probability that a randomly drawn marble is yellow? (Correct: 0.40)
- p102 A bag contains 5-cent, 10-cent, and 20-cent coins. The probability of drawing a 5-cent coin is 0.35, that of drawing a 10-cent coin is 0.25, and that of drawing a 20-cent coin is 0.40. What is the probability that the coin randomly drawn is not a 5-cent coin? (0.65)
- p103 A bag contains 5-cent, 10-cent, and 20-cent coins. The probability of drawing a 5-cent coin is 0.20, that of drawing a 10-cent coin is 0.45, and that of drawing a 20-cent coin is 0.35. What is the probability that the coin randomly drawn is a 5-cent coin or a 20-cent coin? (0.55)
- p104 In a school, 40% of the pupils are boys and 80% of the pupils are right-handed. Suppose that gender and handedness are independent. What is the probability of randomly selecting a right-handed boy? (0.32)
- p105 Given a standard deck containing 32 different cards, what is the probability of not drawing a heart? (0.75)
- p106 A box contains 20 marbles in the following colors: 4 white, 14 green, 2 red. What is the probability that a randomly drawn marble is not white? (0.80)
- p107 A box contains 10 marbles in the following colors: 2 yellow, 5 blue, 3 red. What is the probability that a randomly drawn marble is yellow or blue? (0.70)
- p108 What is the probability of obtaining an even number by throwing a dice? (0.50)
- p109 Given a standard deck containing 32 different cards, what is the probability of drawing a 4 in a black suit? (Responses that round to 0.06 were considered correct.)
- p110 A box contains marbles that are red or yellow, small or large. The probability of drawing a red marble is 0.70 (lab: 0.30), the probability of drawing a small marble is 0.40. Suppose that the color of the marbles is independent of their size. What is the probability of randomly drawing a small marble that is not red? (0.12, lab: 0.28)
- p111 In a garage there are 50 cars. 20 are black and 10 are diesel powered. Suppose that the color of the cars is independent of the kind of fuel. What is the probability that a randomly selected car is not black and it is diesel powered? (0.12)
- p112 A box contains 20 marbles. 10 marbles are red, 6 are yellow and 4 are black. 12 marbles are small and 8 are large. Suppose that the color of the marbles is independent of their size. What is the probability of randomly drawing a small marble that is yellow or red? (0.48)

The twelve problems of the second part (after the learning object):

- p201 A box contains 30 marbles in the following colors: 10 red, 14 yellow, 6 green. What is the probability that a randomly drawn marble is green? (0.20)

- p202 A bag contains 5-cent, 10-cent, and 20-cent coins. The probability of drawing a 5-cent coin is 0.25, that of drawing a 10-cent coin is 0.60, and that of drawing a 20-cent coin is 0.15. What is the probability that the coin randomly drawn is not a 5-cent coin? (0.75)
- p203 A bag contains 5-cent, 10-cent, and 20-cent coins. The probability of drawing a 5-cent coin is 0.35, that of drawing a 10-cent coin is 0.20, and that of drawing a 20-cent coin is 0.45. What is the probability that the coin randomly drawn is a 5-cent coin or a 20-cent coin? (0.80)
- p204 In a school, 70% of the pupils are girls and 10% of the pupils are left-handed. Suppose that gender and handedness are independent. What is the probability of randomly selecting a left-handed girl? (0.07)
- p205 Given a standard deck containing 32 different cards, what is the probability of not drawing a club? (0.75)
- p206 A box contains 20 marbles in the following colors: 6 yellow, 10 red, 4 green. What is the probability that a randomly drawn marble is not yellow? (0.70)
- p207 A box contains 10 marbles in the following colors: 5 blue, 3 red, 2 green. What is the probability that a randomly drawn marble is blue or red? (0.80)
- p208 What is the probability of obtaining an odd number by throwing a dice? (0.50)
- p209 Given a standard deck containing 32 different cards, what is the probability of drawing a 10 in a red suit? (Responses that round to 0.06 were considered correct.)
- p210 A box contains marbles that are green or red, large or small. The probability of drawing a green marble is 0.40, the probability of drawing a large marble is 0.20. Suppose that the color of the marbles is independent of their size. What is the probability of randomly drawing a large marble that is not green? (0.12)
- p211 In a garage there are 50 cars. 15 are white and 20 are diesel powered. Suppose that the color of the cars is independent of the kind of fuel. What is the probability that a randomly selected car is not white and it is diesel powered? (0.28)
- p212 A box contains 20 marbles. 8 marbles are white, 4 are green and 8 are red. 15 marbles are small and 5 are large. Suppose that the color of the marbles is independent of their size. What is the probability of randomly drawing a large marble that is white or green? (0.15)

Further variables:

- time01, ..., time10 the time (in s) spent on each page of the questionnaire. In the lab branch of the study, participants started directly on Page 2.
- b101, ..., b112 the twelve problems of the first part coded as correct (1) or error (0).
- b201, ..., b212 the twelve problems of the second part coded as correct (1) or error (0).

### Source

Data were collected by Pasquale Anselmi and Florian Wickelmaier at the Department of Psychology, University of Tuebingen, in February and March 2010.

### Examples

```
data(probability)

## "Completer" sample
```

```

pb <- probability[!is.na(probability$b201), ]

## Response frequencies for first and second part
N.R1 <- as.pattern(pb[, sprintf("b1%.2i", 1:12)], freq = TRUE)
N.R2 <- as.pattern(pb[, sprintf("b2%.2i", 1:12)], freq = TRUE)

## Conjunctive skill function, one-to-one problem function
sf1 <- read.table(header = TRUE, text = "
  item cp id pb un
    1  0  0  1  0
    2  1  0  0  0
    3  0  0  0  1
    4  0  1  0  0
    5  1  0  1  0
    6  1  0  1  0
    7  0  0  1  1
    8  0  0  1  1
    9  0  1  1  0
   10  1  1  0  0
   11  1  1  1  0
   12  0  1  1  1
")

## Extended skill function
sf2 <- rbind(sf1, read.table(header = TRUE, text = "
  item cp id pb un
    2  0  0  0  1
    3  1  0  0  0
    6  0  0  1  1
    7  1  0  1  0
   12  1  1  1  0
"))

## Delineated knowledge structures
K1 <- delineate(sf1)$K
K2 <- delineate(sf2)$K

## After instructions, fit of knowledge structures improves
sapply(list(N.R1, N.R2), function(n) blim(K1, n)$discrepancy)
sapply(list(N.R1, N.R2), function(n) blim(K2, n)$discrepancy)

```

**Description**

Computes deviance and Pearson residuals for blim objects.

**Usage**

```
## S3 method for class 'blim'
residuals(object, type = c("deviance", "pearson"), ...)
```

**Arguments**

- object            an object of class blim, typically the result of a call to [blim](#).
- type             the type of residuals which should be returned; the alternatives are: "deviance" (default) and "pearson".
- ...              further arguments passed to or from other methods. None are used in this method.

**Details**

See [residuals.glm](#) for details.

**Value**

A named vector of residuals having as many elements as response patterns.

**See Also**

[blim](#), [residuals.glm](#), [plot.blim](#).

**Examples**

```
data(DoignonFalmagne7)
blim1 <- blim(DoignonFalmagne7$K, DoignonFalmagne7$N.R)

sum( resid(blim1)^2 )                    # likelihood ratio G2
sum( resid(blim1, "pearson")^2 )       # Pearson X2
```

**Description**

The 23 fraction problems were presented to 191 first-level middle school students (about 11 to 12 years old). A subset of 13 problems is included in Stefanutti and de Chiusole (2017).

The eight subtraction problems were presented to 294 elementary school students and are described in de Chiusole and Stefanutti (2013).

**Usage**

```
data(schoolarithm)
```

**Format**

fraction17 a person-by-problem indicator matrix representing the responses of 191 persons to 23 problems. The responses are classified as correct (0) or incorrect (1).

The 23 problems were:

- p01  $(\frac{1}{3} + \frac{1}{12}) : \frac{2}{9} = ?$
- p02  $(\frac{3}{2} + \frac{3}{4}) \times \frac{5}{3} - 2 = ?$
- p03  $(\frac{5}{6} + \frac{3}{14}) \times (\frac{19}{8} - \frac{3}{2}) = ?$
- p04  $(\frac{1}{6} + \frac{2}{9}) - \frac{7}{36} = ?$
- p05  $\frac{7}{10} + \frac{9}{10} = ?$
- p06  $\frac{8}{13} + \frac{5}{2} = ?$
- p07  $\frac{8}{12} + \frac{4}{15} = ?$
- p08  $\frac{2}{9} + \frac{5}{6} = ?$
- p09  $\frac{7}{5} + \frac{1}{5} = ?$
- p10  $\frac{2}{7} + \frac{3}{14} = ?$
- p11  $\frac{5}{9} + \frac{1}{6} = ?$
- p12  $(\frac{1}{12} + \frac{1}{3}) \times \frac{24}{15} = ?$
- p13  $2 - \frac{3}{4} = ?$
- p14  $(4 + \frac{3}{4} - \frac{1}{2}) \times \frac{8}{6} = ?$
- p15  $\frac{4}{7} + \frac{3}{4} = \frac{?}{28}$
- p16  $\frac{5}{8} - \frac{3}{16} = \frac{?-?}{16}$
- p17  $\frac{3}{8} + \frac{5}{12} = \frac{? \times 3 + ? \times 5}{24}$
- p18  $\frac{2}{7} + \frac{3}{5} = \frac{5 \times ? + 7 \times ?}{35}$
- p19  $\frac{2}{3} + \frac{6}{9} = \frac{?}{9} = \frac{?}{?}$
- p20 Least common multiple  $lcm(6, 8) = ?$
- p21  $\frac{7}{11} \times \frac{2}{3} = ?$
- p22  $\frac{2}{5} \times \frac{15}{4} = ?$
- p23  $\frac{9}{7} : \frac{2}{3} = ?$

subtraction13 is a data frame consisting of the following components:

School factor; school id.

Classroom factor; class room id.

Gender factor; participant gender.

Age participant age.

R a person-by-problem indicator matrix representing the responses of 294 persons to eight problems.

The eight problems were:

- p1 73 – 58



- p2 317 – 94
- p3 784 – 693
- p4 507 – 49
- p5 253 – 178
- p6 2245 – 418
- p7 156 – 68
- p8 3642 – 753

**Source**

The data were made available by Debora de Chiusole, Andrea Brancaccio, and Luca Stefanutti.

**References**

de Chiusole, D., & Stefanutti, L. (2013). Modeling skill dependence in probabilistic competence structures. *Electronic Notes in Discrete Mathematics*, **42**, 41–48. doi:10.1016/j.endm.2013.05.144

Stefanutti, L., & de Chiusole, D. (2017). On the assessment of learning in competence based knowledge space theory. *Journal of Mathematical Psychology*, **80**, 22–32. doi:10.1016/j.jmp.2017.08.003

**Examples**

```
data(scholarithm)

## Fraction problems used in Sefanutti and de Chiusole (2017)
R <- fraction17[, c(4:8, 10:11, 15:20)]
colnames(R) <- 1:13
N.R <- as.pattern(R, freq = TRUE)

## Conjunctive skill function in Table 1
sf <- read.table(header = TRUE, text = "
  item a b c d e f g h
    1 1 1 1 0 1 1 0 0
    2 1 0 0 0 0 0 1 1
    3 1 1 0 1 1 0 0 0
    4 1 1 0 0 1 1 1 1
    5 1 1 0 0 1 1 0 0
    6 1 1 1 0 1 0 1 1
    7 1 1 0 0 1 1 0 0
    8 1 1 0 0 1 0 1 1
    9 0 1 0 0 1 0 0 0
   10 0 1 0 0 0 0 0 0
   11 0 0 0 0 1 0 0 0
   12 1 1 0 0 1 0 1 1
   13 0 0 0 0 0 0 1 0 0
")
K <- delineate(sf)$K # delineated knowledge structure
blim(K, N.R)

## Subtraction problems used in de Chiusole and Stefanutti (2013)
```

```

N.R <- as.pattern(subtraction13$R, freq = TRUE)

# Skill function in Table 1
# (f) mastering tens and hundreds; (g) mastering thousands; (h1) one borrow;
# (h2) two borrows; (h3) three borrows; (i) mastering the proximity of
# borrows; (j) mastering the presence of the zero; (k) mental calculation
sf <- read.table(header = TRUE, text = "
  item f  g h1 h2 h3 i  j k
    1  0  0  1  0  0  0  0  0
    2  1  0  1  0  0  0  0  0
    3  1  0  1  0  0  1  0  0
    4  1  0  1  1  1  0  1  0
    4  0  0  0  0  0  0  0  1
    5  1  0  1  1  1  1  0  0
    6  1  1  1  1  0  0  0  0
    7  1  0  1  1  1  1  0  0
    8  1  1  1  1  1  0  0  0
")
K <- delineate(sf)$K
blim(K, N.R)

```

---

simulate.blim

*Simulate Responses from Basic Local Independence Models (BLIMs)*


---

## Description

Simulates responses from the distribution corresponding to a fitted blim model object.

## Usage

```

## S3 method for class 'blim'
simulate(object, nsim = 1, seed = NULL, ...)

```

## Arguments

object	an object of class blim, typically the result of a call to <a href="#">blim</a> .
nsim	currently not used.
seed	currently not used.
...	further arguments passed to or from other methods. None are used in this method.

## Details

Responses are simulated in two steps: First, a knowledge state is drawn with probability  $P.K$ . Second, responses are generated by applying [rbinom](#) with probabilities computed from the model object's beta and eta components.

**Value**

A named vector of frequencies of response patterns.

**See Also**

[blim](#), [endm](#).

**Examples**

```
data(DoignonFalmagne7)

m1 <- blim(DoignonFalmagne7$K, DoignonFalmagne7$N.R)
simulate(m1)

## Parametric bootstrap for the BLIM
disc <- replicate(200, blim(m1$K, simulate(m1))$discrepancy)

hist(disc, col = "lightgray", border = "white", freq = FALSE, breaks = 20,
     main = "BLIM parametric bootstrap", xlim = c(.05, .3))
abline(v = m1$discrepancy, lty = 2)

## Parameter recovery for the SLM
m0 <- list( P.K = getSImPK( g = rep(.8, 5),
                          K = DoignonFalmagne7$K,
                          Ko = getKFringe(DoignonFalmagne7$K)),
           beta = rep(.1, 5),
           eta = rep(.1, 5),
           K = DoignonFalmagne7$K,
           ntotal = 800)
class(m0) <- c("slm", "blim")

pars <- replicate(20, coef(slm(m0$K, simulate(m0), method = "ML")))
boxplot(t(pars), horizontal = TRUE, las = 1,
       main = "SLM parameter recovery")

## See ?endm for further examples.
```

---

slm

*Simple Learning Models (SLMs)*


---

**Description**

Fits a simple learning model (SLM) for probabilistic knowledge structures by minimum discrepancy maximum likelihood estimation.

**Usage**

```
slm(K, N.R, method = c("MD", "ML", "MDML"), R = as.binmat(N.R),
    beta = rep(0.1, nitems), eta = rep(0.1, nitems),
    g = rep(0.1, nitems),
    betafix = rep(NA, nitems), etafix = rep(NA, nitems),
    betaequal = NULL, etaequal = NULL,
    randinit = FALSE, incradius = 0,
    tol = 1e-07, maxiter = 10000, zeropad = 16,
    checkK = TRUE)
```

```
getSImPK(g, K, Ko)
```

```
## S3 method for class 'slm'
print(x, P.Kshow = FALSE, parshow = TRUE,
      digits=max(3, getOption("digits") - 2), ...)
```

**Arguments**

K	a state-by-problem indicator matrix representing the knowledge space. An element is one if the problem is contained in the state, and else zero.
N.R	a (named) vector of absolute frequencies of response patterns.
method	MD for minimum discrepancy estimation, ML for maximum likelihood estimation, MDML for minimum discrepancy maximum likelihood estimation.
R	a person-by-problem indicator matrix of unique response patterns. Per default inferred from the names of N.R.
beta, eta, g	vectors of initial values for the error, guessing, and solvability parameters.
betafix, etafix	vectors of fixed error and guessing parameter values; NA indicates a free parameter.
betaequal, etaequal	lists of vectors of problem indices; each vector represents an equivalence class: it contains the indices of problems for which the error or guessing parameters are constrained to be equal. (See Examples.)
randinit	logical, if TRUE then initial parameter values are sampled uniformly with constraints. (See Details.)
incradius	include knowledge states of distance from the minimum discrepant states less than or equal to <code>incradius</code> .
tol	tolerance, stopping criterion for iteration.
maxiter	the maximum number of iterations.
zeropad	the maximum number of items for which an incomplete N.R vector is completed and padded with zeros.
checkK	logical, if TRUE K is checked for well-gradedness.
Ko	a state-by-problem indicator matrix representing the outer fringe for each knowledge state in K; typically the result of a call to <code>getKFringe</code> .

x	an object of class <code>slm</code> , typically the result of a call to <code>slm</code> .
P.Kshow	logical, should the estimated distribution of knowledge states be printed?
parshow	logical, should the estimates of error, guessing, and solvability parameters be printed?
digits	a non-null value for <code>digits</code> specifies the minimum number of significant digits to be printed in values.
...	additional arguments passed to other methods.

### Details

See Doignon and Falmagne (1999) for details on the simple learning model (SLM) for probabilistic knowledge structures. The model requires a well-graded knowledge space  $K$ .

An `slm` object inherits from class `blim`. See `blim` for details on the function arguments. The helper function `getS1mPK` returns the distribution of knowledge states  $P.K$ .

### Value

An object of class `slm` and `blim`. It contains all components of a `blim` object. In addition, it includes:

g	the vector of estimates of the solvability parameters.
---	--

### References

Doignon, J.-P., & Falmagne, J.-C. (1999). *Knowledge spaces*. Berlin: Springer.

### See Also

[blim](#), [simulate.blim](#), [getKFringe](#), [is.downgradable](#)

### Examples

```
data(DoignonFalmagne7)
K <- DoignonFalmagne7$K # well-graded knowledge space
N.R <- DoignonFalmagne7$N.R # frequencies of response patterns

## Fit simple learning model (SLM) by different methods
slm(K, N.R, method = "MD") # minimum discrepancy estimation
slm(K, N.R, method = "ML") # maximum likelihood estimation by EM
slm(K, N.R, method = "MDML") # MDML estimation

## Compare SLM and BLIM
m1 <- slm(K, N.R, method = "ML")
m2 <- blim(K, N.R, method = "ML")
anova(m1, m2)
```

**Description**

Taagepera et al. (1997) applied knowledge space theory to specific science problems. The density test was administered to 2060 students, the conservation of matter test to 1620 students. A subtest of five items each is included here. The response frequencies were reconstructed from histograms in the paper.

**Usage**

```
data(Taagepera)
```

**Format**

Two lists, each consisting of two components:

density97 a list with components K and N.R for the density test.

matter97 a list with components K and N.R for the conservation of matter test.

K a state-by-problem indicator matrix representing the hypothetical knowledge structure. An element is one if the problem is contained in the state, and else zero.

N.R a named numeric vector. The names denote response patterns, the values denote their frequencies.

**Source**

Taagepera, M., Potter, F., Miller, G.E., & Lakshminarayan, K. (1997). Mapping students' thinking patterns by the use of knowledge space theory. *International Journal of Science Education*, **19**(3), 283–302. doi:10.1080/0950069970190303

**Examples**

```
data(Taagepera)
density97$K      # density test knowledge structure
density97$N.R    # density test response patterns
matter97$K       # conservation of matter knowledge structure
matter97$N.R     # conservation of matter response patterns
```

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