Package ‘statConfR’

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Type Package

Title Models of Decision Confidence and Metacognition

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Description Provides fitting functions and other tools for decision confidence and metacognition researchers, including meta-d'/d', often considered to be the gold standard to measure metacognitive efficiency.
Also allows to fit several static models of decision making and confidence to test the assumptions underlying meta-d'/d' and which may serve as an alternative when the assumptions of meta-d'/d' do not hold. See also Rausch et al. (2023) <doi:10.1037/met0000634>.

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URL https://github.com/ManuelRausch/StatConfR

BugReports https://github.com/ManuelRausch/StatConfR/issues

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R topics documented:

`fitConf` *Fit a static confidence model to data*

Description

This function fits one static model of decision confidence to binary choices and confidence judgments. It calls a corresponding fitting function for the selected model.

Usage

```
fitConf(data, model = "SDT", nInits = 5, nRestart = 4)
```

Arguments

`data` a `data.frame` where each row is one trial, containing following variables:

- `diffCond` (optional; different levels of discriminability, should be a factor with levels ordered from hardest to easiest),
- `rating` (discrete confidence judgments, should be a factor with levels ordered from lowest confidence to highest confidence; otherwise will be transformed to factor with a warning),
- `stimulus` (stimulus category in a binary choice task, should be a factor with two levels, otherwise it will be transformed to a factor with a warning),
- `correct` (encoding whether the response was correct; should be 0 for incorrect responses and 1 for correct responses)

`model` `character` of length 1. Models implemented so far: 'WEV', 'SDT', 'GN', 'PDA', 'IG', 'ITGc', 'ITGcm', 'logN', and 'logWEV'.

`nInits` `integer`. Number of initial values used for maximum likelihood optimization. Defaults to 5.

`nRestart` `integer`. Number of times the optimization algorithm is restarted. Defaults to 4.

Details

The fitting routine first performs a coarse grid search to find promising starting values for the maximum likelihood optimization procedure. Then the best `nInits` parameter sets found by the grid search are used as the initial values for separate runs of the Nelder-Mead algorithm implemented in `optim`. Each run is restarted `nRestart` times.

Mathematical description of models:

The computational models are all based on signal detection theory (Green & Swets, 1966). It is assumed that participants select a binary discrimination response R about a stimulus S. Both S and R can be either -1 or 1. R is considered correct if $S = R$. In addition, we assume that there are K different levels of stimulus discriminability in the experiment, i.e. a physical variable that makes the discrimination task easier or harder. For each level of discriminability, the function fits a different discrimination sensitivity parameter d_k. If there is more than one sensitivity parameter, we assume that the sensitivity parameters are ordered such as $0 < d_1 < ... < d_K$. The models assume that the stimulus generates normally distributed sensory evidence x with mean $S \times d_k/2$ and variance of 1. The sensory evidence x is compared to a decision criterion c to generate a discrimination response R, which is 1, if x exceeds c and -1 else. To generate confidence, it is assumed that the confidence variable y is compared to another set of criteria $\theta_{R,i}, i = 1, ..., L-1$, depending on the discrimination response R to produce a L-step discrete confidence response. The number of thresholds will be inferred from the number of steps in the `rating` column of `data`. Thus, the parameters shared between all models are:

- sensitivity parameters d_1,...,d_K (K: number of difficulty levels)
- decision criterion c
- confidence criterion $\theta_{-1,1}$,$\theta_{-1,2}$, ..., $\theta_{-1,L-1}$, $\theta_{1,1}$, $\theta_{1,2}$,..., $\theta_{1,L-1}$ (L: number of confidence categories available for confidence ratings)

How the confidence variable y is computed varies across the different models. The following models have been implemented so far:

Signal Detection Rating Model (SDT)*:*
According to SDT, the same sample of sensory evidence is used to generate response and confidence, i.e., $y = x$ and the confidence criteria span from the left and right side of the decision criterion c (Green & Swets, 1966).

Gaussian Noise Model (GN)*:*
According to the model, y is subject to additive noise and assumed to be normally distributed around the decision evidence value x with a standard deviation σ (Maniscalco & Lau, 2016). The parameter σ is a free parameter.

Weighted Evidence and Visibility model (WEV)*:*
WEV assumes that the observer combines evidence about decision-relevant features of the stimulus with the strength of evidence about choice-irrelevant features to generate confidence (Rausch et al., 2018). Here, we use the version of the WEV model used by Rausch et al. (2023), which assumes that y is normally distributed with a mean of $(1 - w) \times x + w \times d_k \times R$ and standard deviation σ. The parameter σ quantifies the amount of unsystematic variability contributing to confidence judgments but not to the discrimination judgments. The parameter w represents the weight that is put on the choice-irrelevant features in the confidence judgment. w and σ are fitted in addition to the set of shared parameters.

Post-decisional accumulation model (PDA)*:*

PDA represents the idea of on-going information accumulation after the discrimination choice (Rausch et al., 2018). The parameter b indicates the amount of additional accumulation. The confidence variable is normally distributed with mean $x + S \times d_k \times b$ and variance b. For this model the parameter b is fitted in addition to the set of shared parameters.

Independent Gaussian Model (IG)*:*
According to IG, y is sampled independently from x (Rausch & Zehetleitner, 2017). y is normally distributed with a mean of $a \times d_k$ and variance of 1 (again as it would scale with m). The free parameter m represents the amount of information available for confidence judgment relative to amount of evidence available for the discrimination decision and can be smaller as well as greater than 1.

Independent Truncated Gaussian Model: HMetad-Version (ITGc)*:*
According to the version of ITG consistent with the HMetad-method (Fleming, 2017; see Rausch et al., 2023), y is sampled independently from x from a truncated Gaussian distribution with a location parameter of $S \times d_k \times m/2$ and a scale parameter of 1. The Gaussian distribution of y is truncated in a way that it is impossible to sample evidence that contradicts the original decision: If $R = -1$, the distribution is truncated to the right of c. If $R = 1$, the distribution is truncated to the left of c. The additional parameter m represents metacognitive efficiency, i.e., the amount of information available for confidence judgments relative to amount of evidence available for discrimination decisions and can be smaller as well as greater than 1.

Independent Truncated Gaussian Model: Meta-d'-Version (ITGcm)*:*
According to the version of the ITG consistent with the original meta-d' method (Maniscalco & Lau, 2012, 2014; see Rausch et al., 2023), y is sampled independently from x from a truncated Gaussian distribution with a location parameter of $S \times d_k \times m/2$ and a scale parameter of 1. If $R = -1$, the distribution is truncated to the right of $m \times c$. If $R = 1$, the distribution is truncated to the left of $m \times c$. The additional parameter m represents metacognitive efficiency, i.e., the amount of information available for confidence judgments relative to amount of evidence available for the discrimination decision and can be smaller as well as greater than 1.

Logistic Noise Model (logN)*:*
According to logN, the same sample of sensory evidence is used to generate response and confidence, i.e., $y = x$ just as in SDT (Shekhar & Rahnev, 2021). However, according to logN, the confidence criteria are not assumed to be constant, but instead they are affected by noise drawn from a lognormal distribution. In each trial, $\theta_{-1,i}$ is given by $c - \epsilon_i$. Likewise, $\theta_{1,i}$ is given by $c + \epsilon_i$. ϵ_i is drawn from a lognormal distribution with the location parameter $\mu_{R,i} = log(|\overline{\theta}_{R,i} - c|) - 0.5 \times \sigma^2$ and scale parameter σ. σ is a free parameter designed to quantify metacognitive ability. It is assumed that the criterion noise is perfectly correlated across confidence criteria, ensuring that the confidence criteria are always perfectly ordered. Because $\theta_{-1,1}$, ..., $\theta_{-1,L-1}$, $\theta_{1,1}$, ..., $\theta_{1,L-1}$ change from trial to trial, they are not estimated as free parameters. Instead, we estimate the means of the confidence criteria, i.e., $\overline{\theta}_{-1,1}, ..., \overline{\theta}_{-1,L-1}, \overline{\theta}_{1,1}, ...\overline{\theta}_{1,L-1}$, as free parameters.

Logistic Weighted Evidence and Visibility model (logWEV)*:*
logWEV is a combination of logN and WEV proposed by Shekhar and Rahnev (2023). Conceptually, logWEV assumes that the observer combines evidence about decision-relevant features of the stimulus with the strength of evidence about choice-irrelevant features (Rausch et al., 2018). The model also assumes that noise affecting the confidence decision variable is lognormal in accordance with Shekhar and Rahnev (2021). According to logWEV, the confidence decision variable y is equal to $y^* \times R$. y^* is sampled from a lognormal distribution with a location parameter of $(1 - w) \times x \times R + w \times d_k$ and a scale parameter of σ. The parameter

σ quantifies the amount of unsystematic variability contributing to confidence judgments but not to the discrimination judgments. The parameter w represents the weight that is put on the choice-irrelevant features in the confidence judgment. w and σ are fitted in addition to the set of shared parameters.

Value

Gives data frame with one row and columns for the fitted parameters of the selected model as well as additional information about the fit (`negLogLik` (negative log-likelihood of the final set of parameters), `k` (number of parameters), `N` (number of data rows), `AIC` (Akaike Information Criterion; Akaike, 1974), `BIC` (Bayes information criterion; Schwarz, 1978), and `AICc` (AIC corrected for small samples; Burnham & Anderson, 2002))

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Examples

```
# 1. Select one subject from the masked orientation discrimination experiment
data <- subset(MaskOri, participant == 1)
head(data)

# 2. Use fitting function

  # Fitting takes some time to run:
  FitFirstSbjWEV <- fitConf(data, model="WEV")
```

`fitConfModels` *Fit several static confidence models to multiple participants*

Description

This function is a wrapper of the function `fitConf`. It calls the function for every possible combination of model in the `model` argument and participant in the `data`, respectively. See the Details for more information about the parameters.

Usage

```
fitConfModels(data, models = "all", nInits = 5, nRestart = 4,
  .parallel = FALSE, n.cores = NULL)
```

Arguments

`data` a `data.frame` where each row is one trial, containing following variables:

- `diffCond` (optional; different levels of discriminability, should be a factor with levels ordered from hardest to easiest),
- `rating` (discrete confidence judgments, should be a factor with levels ordered from lowest confidence to highest confidence; otherwise will be transformed to factor with a warning),
- `stimulus` (stimulus category in a binary choice task, should be a factor with two levels, otherwise it will be transformed to a factor with a warning),
- `correct` (encoding whether the response was correct; should be 0 for incorrect responses and 1 for correct responses)
- `participant` (giving the subject ID; the models given in the second argument are fitted for each subject individually.

`models`	`character`. Models implemented so far: 'WEV', 'SDT', 'GN', 'PDA', 'IG', 'ITGc', 'ITGcm', 'logN', and 'logWEV'. Alternatively, if `model="all"` (default), all implemented models will be fit.
`nInits`	`integer`. Number of initial values used for maximum likelihood optimization. Defaults to 5.
`nRestart`	`integer`. Number of times the optimization is restarted. Defaults to 4.
`.parallel`	`logical`. Whether to parallelize the fitting over models and participant (default: FALSE)
`n.cores`	`integer`. Number of cores used for parallelization. If NULL (default), the available number of cores -1 will be used.

Details

The fitting routine first performs a coarse grid search to find promising starting values for the maximum likelihood optimization procedure. Then the best `nInits` parameter sets found by the grid search are used as the initial values for separate runs of the Nelder-Mead algorithm implemented in `optim`. Each run is restarted `nRestart` times.

Mathematical description of models:

The computational models are all based on signal detection theory (Green & Swets, 1966). It is assumed that participants select a binary discrimination response R about a stimulus S. Both S and R can be either -1 or 1. R is considered correct if $S = R$. In addition, we assume that there are K different levels of stimulus discriminability in the experiment, i.e. a physical variable that makes the discrimination task easier or harder. For each level of discriminability, the function fits a different discrimination sensitivity parameter d_k. If there is more than one sensitivity parameter, we assume that the sensitivity parameters are ordered such as $0 < d_1 < d_2 < ... < d_K$. The models assume that the stimulus generates normally distributed sensory evidence x with mean $S \times d_k/2$ and variance of 1. The sensory evidence x is compared to a decision criterion c to generate a discrimination response R, which is 1, if x exceeds c and -1 else. To generate confidence, it is assumed that the confidence variable y is compared to another set of criteria $\theta_{R,i}, i = 1, 2, ..., L-1$, depending on the discrimination response R to produce a L-step discrete confidence response. The number of thresholds will be inferred from the number of steps in the `rating` column of `data`. Thus, the parameters shared between all models are:

- sensitivity parameters d_1,...,d_K (K: number of difficulty levels)
- decision criterion c
- confidence criterion $\theta_{-1,1}$,$\theta_{-1,2}$, ..., $\theta_{-1,L-1}$, $\theta_{1,1}$, $\theta_{1,2}$,..., $\theta_{1,L-1}$ (L: number of confidence categories available for confidence ratings)

How the confidence variable y is computed varies across the different models. The following models have been implemented so far:

Signal Detection Rating Model (SDT):

According to SDT, the same sample of sensory evidence is used to generate response and confidence, i.e., $y = x$ and the confidence criteria span from the left and right side of the decision criterion c(Green & Swets, 1966).

Gaussian Noise Model (GN):

According to the model, y is subject to additive noise and assumed to be normally distributed around the decision evidence value x with a standard deviation σ(Maniscalco & Lau, 2016). σ is an additional free parameter.

Weighted Evidence and Visibility model (WEV):
WEV assumes that the observer combines evidence about decision-relevant features of the stimulus with the strength of evidence about choice-irrelevant features to generate confidence (Rausch et al., 2018). Thus, the WEV model assumes that y is normally distributed with a mean of $(1-w) \times x + w \times d_k \times R$ and standard deviation σ. The standard deviation quantifies the amount of unsystematic variability contributing to confidence judgments but not to the discrimination judgments. The parameter w represents the weight that is put on the choice-irrelevant features in the confidence judgment. w and σ are fitted in addition to the set of shared parameters.

Post-decisional accumulation model (PDA):
PDA represents the idea of on-going information accumulation after the discrimination choice (Rausch et al., 2018). The parameter a indicates the amount of additional accumulation. The confidence variable is normally distributed with mean $x + S \times d_k \times a$ and variance a. For this model the parameter a is fitted in addition to the shared parameters.

Independent Gaussian Model (IG):
According to IG, y is sampled independently from x (Rausch & Zehetleitner, 2017). y is normally distributed with a mean of $a \times d_k$ and variance of 1 (again as it would scale with m). The additional parameter m represents the amount of information available for confidence judgment relative to amount of evidence available for the discrimination decision and can be smaller as well as greater than 1.

Independent Truncated Gaussian Model: HMetad-Version (ITGc):
According to the version of ITG consistent with the HMetad-method (Fleming, 2017; see Rausch et al., 2023), y is sampled independently from x from a truncated Gaussian distribution with a location parameter of $S \times d_k \times m/2$ and a scale parameter of 1. The Gaussian distribution of y is truncated in a way that it is impossible to sample evidence that contradicts the original decision: If $R = -1$, the distribution is truncated to the right of c. If $R = 1$, the distribution is truncated to the left of c. The additional parameter m represents metacognitive efficiency, i.e., the amount of information available for confidence judgments relative to amount of evidence available for discrimination decisions and can be smaller as well as greater than 1.

Independent Truncated Gaussian Model: Meta-d'-Version (ITGcm):
According to the version of the ITG consistent with the original meta-d' method (Maniscalco & Lau, 2012, 2014; see Rausch et al., 2023), y is sampled independently from x from a truncated Gaussian distribution with a location parameter of $S \times d_k \times m/2$ and a scale parameter of 1. If $R = -1$, the distribution is truncated to the right of $m \times c$. If $R = 1$, the distribution is truncated to the left of $m \times c$. The additional parameter m represents metacognitive efficiency, i.e., the amount of information available for confidence judgments relative to amount of evidence available for the discrimination decision and can be smaller as well as greater than 1.

Logistic Noise Model (logN):
According to logN, the same sample of sensory evidence is used to generate response and confidence, i.e., $y = x$ just as in SDT (Shekhar & Rahnev, 2021). However, according to logN, the confidence criteria are not assumed to be constant, but instead they are affected by noise drawn from a lognormal distribution. In each trial, $\theta_{-1,i}$ is given by $c - \epsilon_i$. Likewise, $\theta_{1,i}$ is given by $c + \epsilon_i$. ϵ_i is drawn from a lognormal distribution with the location parameter $\mu_{R,i} = log(|\overline{\theta}_{R,i} - c|) - 0.5 \times \sigma^2$ and scale parameter σ. σ is a free parameter designed to quantify metacognitive ability. It is assumed that the criterion noise is perfectly correlated across confidence criteria, ensuring that the confidence criteria are always perfectly ordered. Because $\theta_{-1,1}$, ..., $\theta_{-1,L-1}$, $\theta_{1,1}$, ..., $\theta_{1,L-1}$ change from trial to trial, they are not

estimated as free parameters. Instead, we estimate the means of the confidence criteria, i.e., $\overline{\theta}_{-1,1}, ..., \overline{\theta}_{-1,L-1}, \overline{\theta}_{1,1}, ...\overline{\theta}_{1,L-1}$, as free parameters.

Logistic Weighted Evidence and Visibility model (logWEV)*:*
logWEV is a combination of logN and WEV proposed by Shekhar and Rahnev (2023). Conceptually, logWEV assumes that the observer combines evidence about decision-relevant features of the stimulus with the strength of evidence about choice-irrelevant features (Rausch et al., 2018). The model also assumes that noise affecting the confidence decision variable is lognormal in accordance with Shekhar and Rahnev (2021). According to logWEV, the confidence decision variable is y is equal to $y^* \times R$. y^* is sampled from a lognormal distribution with a location parameter of $(1 - w) \times x \times R + w \times d_k$ and a scale parameter of σ. The parameter σ quantifies the amount of unsystematic variability contributing to confidence judgments but not to the discrimination judgments. The parameter w represents the weight that is put on the choice-irrelevant features in the confidence judgment. w and σ are fitted in addition to the set of shared parameters.

Value

Gives data frame with one row for each combination of model and participant and columns for the estimated parameters. Additional information about the fit is provided in additional columns:

- `negLogLik` (negative log-likelihood of the best-fitting set of parameters),
- `k` (number of parameters),
- `N` (number of trials),
- `AIC` (Akaike Information Criterion; Akaike, 1974),
- `BIC` (Bayes information criterion; Schwarz, 1978),
- `AICc` (AIC corrected for small samples; Burnham & Anderson, 2002) If length(models) > 1 or models == "all", there will be three additional columns:
- `wAIC`: Akaike weights based on AIC,
- `wAIC`: Akaike weights based on AICc,
- `wBICc`: Schwarz weights (see Burnham & Anderson, 2002)

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Shekhar, M., & Rahnev, D. (2023). How Do Humans Give Confidence? A Comprehensive Comparison of Process Models of Perceptual Metacognition. Journal of Experimental Psychology: General. doi:10.1037/xge0001524

Examples

```
# 1. Select two subjects from the masked orientation discrimination experiment
data <- subset(MaskOri, participant %in% c(1:2))
head(data)

# 2. Fit some models to each subject of the masked orientation discrimination experiment

  # Fitting several models to several subjects takes quite some time
  # If you want to fit more than just two subjects,
  # we strongly recommend setting .parallel=TRUE
  Fits <- fitConfModels(data, models = c("SDT", "ITGc"), .parallel = FALSE)
```

`fitMetaDprime` *Fits meta-d' and meta-d'/d' ratios for data from one or several subjects*

Description

This function computes meta-d' and meta-d'/d' for each participant in the `data`, respectively.

Usage

```
fitMetaDprime(data, model = "ML", nInits = 5, nRestart = 3,
  .parallel = FALSE, n.cores = NULL)
```

Arguments

`data`	a `data.frame` where each row is one trial, containing following variables: • `rating` (discrete confidence judgments, should be given as factor; otherwise will be transformed to factor with a warning), • `stimulus` (stimulus category in a binary choice task, should be a factor with two levels, otherwise it will be transformed to a factor with a warning), • `correct` (encoding whether the response was correct; should be 0 for incorrect responses and 1 for correct responses) • `participant` (giving the subject ID; the models given in the second argument are fitted for each subject individually.
`model`	`character` of length 1. Either "ML" to use the original model specification by Maniscalco and Lau (2012, 2014) or "F" to use the model specification by Fleming (2017)'s HmetaD method. Defaults to "ML"
`nInits`	`integer`. Number of initial values used for maximum likelihood optimization. Defaults to 5.
`nRestart`	`integer`. Number of times the optimization is restarted. Defaults to 3.
`.parallel`	`logical`. Whether to parallelize the fitting over models and participant (default: FALSE)
`n.cores`	`integer`. Number of cores used for parallelization. If NULL (default), the available number of cores -1 will be used.

Details

The function computes meta-d' and meta-d'/d' either using the hypothetical signal detection model assumed by Maniscalco and Lau (2012, 2014) or the one assumed by Fleming (2014). The fitting routine first performs a coarse grid search to find promising starting values for the maximum likelihood optimization procedure. Then the best `nInits` parameter sets found by the grid search are used as the initial values for separate runs of the Nelder-Mead algorithm implemented in `optim`. Each run is restarted `nRestart` times. Warning: meta-d'/d' is only guaranteed to be unbiased from discrimination sensitivity, discrimination bias, and confidence criteria if the data is generated according to the independent truncated Gaussian model (see Rausch et al., 2023).

Value

Gives data frame with rows for each participant and columns dprime, c, metaD, and Ratio

- dprime is the discrimination sensitivity index d, calculated using a standard SDT formula
- c is the discrimination bias c, calculated using a standard SDT formula
- metaD is meta-d', discrimination sensitivity estimated from confidence judgments conditioned on the response
- Ratio is meta-d'/d', a quantity usually referred to as metacognitive efficiency.

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Rausch, M., Hellmann, S., & Zehetleitner, M. (2023). Measures of metacognitive efficiency across cognitive models of decision confidence. Psychological Methods. doi: 10.31234/osf.io/kdz34

Examples

```
# 1. Select two subject from the masked orientation discrimination experiment
data <- subset(MaskOri, participant %in% c(1:2))
head(data)

# 2. Fit meta-d/d for each subject in data
MetaDs <- fitMetaDprime(data, model="F", .parallel = FALSE)
```

`MaskOri` *Data of 16 participants in a masked orientation discrimination experiment (Hellmann et al., 2023, Exp. 1)*

Description

In each trial, participants were shown a sinusoidal grating oriented either horizontally or vertically, followed by a mask after varying stimulus-onset-asynchronies. Participants were instructed to report the orientation and their degree of confidence as accurately as possible

Usage

```
data(MaskOri)
```

Format

A data.frame with 25920 rows representing different trials and 5 variables:

participant integer values as unique participant identifier

stimulus orientation of the grating (90: vertical, 0: horizontal)

correct 0-1 column indicating whether the discrimination response was correct (1) or not (0)

rating 0-4 confidence rating on a continous scale binned into five categories

diffCond stimulus-onset-asynchrony in ms (i.e. time between stimulus and mask onset)

trialNo Enumeration of trials per participant

Examples

```
data(MaskOri)
summary(MaskOri)
```

`simConf` *Simulate data according to a static model of confidence*

Description

Simulate data according to a static model of confidence

Usage

```
simConf(model = "SDT", paramDf)
```

Arguments

`model` — `character` of length 1. Models implemented so far: 'WEV', 'SDT', 'GN', 'PDA', 'IG', 'ITGc', 'ITGcm', 'logN', and 'logWEV'.

`paramDf` — a `data.frame` that contains all parameters to simulate a data set, with one row and the different parameters in different columns. Which parameters are needed depends on the specific model:

- `N` (the number of trials be simulated),
- `participant` (optional, the participant ID of each parameter set. Should be unique to each row),
- `d_1`, `d_2`, ... (sensitivity parameters. The number of sensitivity parameters determines the number of levels of discriminability),
- `c` (discrimination bias),
- `theta_minus.1`, `theta_minus.2`, ... (confidence criteria associated with the response R = -1. The function simulates one more confidence category than there are confidence criteria),
- `theta_plus.1`, `theta_plus.2`, ... (confidence criteria associated with the response R = 1. The function simulates one more confidence category than there are confidence criteria),
- `w` (only for models WEV and logWEV: the visibility weighting parameter, bounded between 0 and 1),
- `sigma` (only for models WEV, GN, logN, and logWEV: confidence noise, bounded between 0 and Inf),

- m (only for IG, ITGm, and ITGcm: metacognitive efficiency parameter, bounded between 0 and Inf),
- b (only for PDA: postdecisional accumulation parameter, bounded between 0 and Inf),
- M_theta_minus.1, M_theta_minus.2, ... (only for logN: Mean confidence criteria associated with the response R = -1),
- M_theta_plus.1, M_theta_plus.2,... (only for logN: Mean confidence criteria associated with the response R = 1).

Details

see fitConf for a detailed description of the different models.

Value

a dataframe with N rows, and the columns stimulus, correct and rating. If more than 1 sensitivity parameter is provided, there is diffCond.

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Examples

```
# 1. define some parameters
paramDf <- data.frame(d_1 = 0, d_2 = 2, d_3 = 4,c = .0,
theta_minus.2 = -2, theta_minus.1 = -1, theta_plus.1 = 1, theta_plus.2 = 2,
sigma = 1/2, w = 0.5, N = 500)
# 2. Simulate dataset
SimulatedData <- simConf(model = "WEV", paramDf)
```

Index