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:10.31234/osf.io/kdz34>.

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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 empirical data. It calls a corresponding fitting function for the selected model.

Usage

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

Arguments

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

- `condition` (optional; different levels of discriminability, should be a factor with levels ordered from hardest to easiest),
- `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)

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

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. 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 (although the function outputs use A and B to refer to the two stimulus categories when it is convenient). 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 task easier or harder. For each level of discriminability, the function fits a different discrimination sensitivity parameter 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 threshold θ to generate a discrimination response R, which is 1, if x exceeds θ and -1 else. To generate confidence, it is assumed that the confidence variable y is compared to another set of thresholds $c_{D,i}, D = A, B, i = 1, ..., L-1$, depending on the discrimination decision D 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`. The parameters shared between all models are therefore:

- sensitivity parameters d_1,...,d_K (K: number of difficulty levels)
- decision threshold θ
- confidence threshold $c_{A,1}$,...$c_{A,L-1}$,$c_{B,1}$,... $c_{B,L-1}$ (L: number of steps 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 the signal detection rating model (Green & Swets, 1966), the same sample of sensory evidence is used to generate response and confidence, i.e., $y = x$ and the confidence thresholds span from the left and right side of the decision threshold θ.

Gaussian Noise Model (Noisy):
According to the Gaussian noise model (Maniscalco & Lau, 2016), y is subject to additive noise and assumed to be normally distributed around the decision evidence value x with some standard deviation σ. 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 common 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 common parameters.

Independent Gaussian Model (IG):
According to the Independent Gaussian Model, y is sampled independently from x (Rausch & Zehetleitner, 2017). It is normally distributed with a mean of $a \times d_k$ and variance of 1 (again as it would scale with a). The additional parameter a 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 - Version Fleming (ITGc):
According to the version of the Independent Truncated Gaussian Models 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 θ. If $R = 1$, the distribution is truncated to the left of θ. 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 - Version Maniscalco and Lau (ITGcm):
According to the version of the Independent Truncated Gaussian Models consistent with the original meta-d' method (Maniscalco & Lau, 2012, 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 $m \times \theta$. If $R = 1$, the distribution is truncated to the left of $m \times \theta$. 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.

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), `BIC`, `AICc` and `AIC`)

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References

Fleming, S. M. (2017). HMeta-d: Hierarchical Bayesian estimation of metacognitive efficiency from confidence ratings. Neuroscience of Consciousness, 1, 1–14. doi: 10.1093/nc/nix007

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Maniscalco, B., & Lau, H. (2016). The signal processing architecture underlying subjective reports of sensory awareness. Neuroscience of Consciousness, 1, 1–17. doi: 10.1093/nc/niw002

Rausch, M., Hellmann, S., & Zehetleitner, M. (2018). Confidence in masked orientation judgments is informed by both evidence and visibility. Attention, Perception, and Psychophysics, 80(1), 134–154. doi: 10.3758/s13414-017-1431-5

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

Rausch, M., & Zehetleitner, M. (2017). Should metacognition be measured by logistic regression? Consciousness and Cognition, 49, 291–312. doi: 10.1016/j.concog.2017.02.007

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:
  FitFirstSbjSDT <- fitConf(data, model=c("SDT"))
```

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

Description

This function is a wrapper of the function `fitConf` (see there for more information). 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:

- `condition` (optional; different levels of discriminability, should be a factor with levels ordered from hardest to easiest),
- `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.

`models` `character` vector of models to be fit for each participant. Models implemented so far: 'WEV', 'SDT', 'Noisy', 'PDA', 'IG', 'ITGc' and 'ITGcm' 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:

This section contains a detailed mathematical description of all models implemented in the package.

The computational models are all based on signal detection theory. Assume that there are k different levels of difficulty manipulated in the (and the levels are given by the `condition` column in the `data`) and that the `stimulus` column indicated the identity of the true stimulus S being either -1 or 1. Then, for each level of difficulty , a value for the sensitivity d_k is fit. The models assume that the stimulus generates normally distributed sensory evidence x with mean $Sd_k/2$ and variance σ_k (see below). The sensory evidence x is compared to a decision threshold θ to generate a choice response R, which is 1, if x exceeds θ and -1 else. (In the output of the functions this will be A and B respectively.) To generate confidence, the confidence variable y is compared to another set of thresholds $c_{D,i}, D = A, B, i = 1, ..., L - 1$, depending on the initial choice D to produce a L-step discrete confidence response. The number of thresholds will be inferred by the number of steps in the `rating` column of `data`. The parameters common to all models are thus:

- sensitivity parameters d_1,...,d_k (k: number of difficulty levels)
- choice threshold θ
- confidence threshold $c_{A,1}$,...$c_{A,L-1}$,$c_{B,1}$,... $c_{B,L-1}$ (L: number of steps 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 the signal detection rating model (Green & Swets, 1966), the same sample of sensory evidence is used to generate response and confidence, i.e., $y = x$ and the confidence thresholds span from the left and right side of the decision threshold θ.

Gaussian Noise Model (Noisy)*:*

According to the Gaussian noise model (Maniscalco & Lau, 2016), y is subject to additive noise and assumed to be normally distributed around the decision evidence value x with some standard deviation σ. 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 common 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 common parameters.

Independent Gaussian Model (IG):
According to the Independent Gaussian Model, y is sampled independently from x (Rausch & Zehetleitner, 2017). It is normally distributed with a mean of $a \times d_k$ and variance of 1 (again as it would scale with a). The additional parameter a 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 - Version Fleming (ITGc):
According to the version of the Independent Truncated Gaussian Models 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 θ. If $R = 1$, the distribution is truncated to the left of θ. 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 - Version Maniscalco and Lau (ITGcm):
According to the version of the Independent Truncated Gaussian Models consistent with the original meta-d' method (Maniscalco & Lau, 2012, 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 $m \times \theta$. If $R = 1$, the distribution is truncated to the left of $m \times \theta$. 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.

Value

Gives data frame with rows for each model-participant combination and columns for the different parameters as fitted result as well as additional information about the fit (`negLogLik` (for final parameters), `k` (number of parameters), `N` (number of data rows), `BIC`, `AICc` and `AIC`)

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References

Fleming, S. M. (2017). HMeta-d: Hierarchical Bayesian estimation of metacognitive efficiency from confidence ratings. Neuroscience of Consciousness, 1, 1–14. doi: 10.1093/nc/nix007

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Rausch, M., Hellmann, S., & Zehetleitner, M. (2018). Confidence in masked orientation judgments is informed by both evidence and visibility. Attention, Perception, and Psychophysics, 80(1), 134–154. doi: 10.3758/s13414-017-1431-5

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

Rausch, M., & Zehetleitner, M. (2017). Should metacognition be measured by logistic regression? Consciousness and Cognition, 49, 291–312. doi: 10.1016/j.concog.2017.02.007

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("ITGc", "SDT"), .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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References

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Rausch, M., Hellmann, S., & Zehetleitner, M. (2023). Measures of metacognitive efficiency across cognitive models of decision confidence (Preprint). PsyArXiv. 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 36 participants in a masked orientation discrimination experiment*

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 34,430 rows and 8 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 factor 4-point confidence scale. The four confidence categories were labelled as "not at all", "a little", "nearly sure" and "sure".

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

gender gender of the participant: "w" for female; "m" for male participants

age the age of participants in years

trialNo Enumeration of trials per participant

Examples

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

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