

Package ‘BoundIRT’

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Title Fit Bounded Continuous Item Response Theory Models to Data

Version 0.5.0

Description Bounded continuous data are encountered in many areas of test application.

Examples include visual analogue scales used in the measurement of personality, mood, depression, and quality of life; item response times from tests with item deadlines; confidence ratings; and pain intensity ratings. Using this package, item response theory (IRT) models suitable for bounded continuous item scores can be fitted to data within a Bayesian framework.

The package draws on posterior sampling facilities provided by R-package ‘rstan’ (Stan Development Team, 2025)<<https://mc-stan.org/>>.

Available models include the Beta IRT model by Noel and Dauvier (2007)<[doi:10.1177/0146621605287691](https://doi.org/10.1177/0146621605287691)>, the continuous response model by Samejima (1973)<[doi:10.1007/BF03372160](https://doi.org/10.1007/BF03372160)>, the unbounded normal model by Meltenbergh (1994)<[doi:10.1207/s15327906mbr2903_2](https://doi.org/10.1207/s15327906mbr2903_2)>,

and the Simplex IRT model by Flores et al. (2020)<[doi:10.1007/978-3-030-43469-4_8](https://doi.org/10.1007/978-3-030-43469-4_8)>. All models can be

fitted with or without zero-one inflation (Molenaar et al., 2022)<[doi:10.3102/10769986221108455](https://doi.org/10.3102/10769986221108455)>.

Model fit comparisons can be conducted using the Watanabe-Akaike information criterion (WAIC), leave-one-out cross-validation information criterion (LOOIC) and the fully marginalized likelihood (i.e., Bayes factors).

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BoundIRT-package	<i>The 'BoundIRT' package.</i>
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Description

Bounded continuous data are encountered in many areas of test application. Examples include visual analogue scales used in the measurement of personality, mood, depression, and quality of life; item response times from tests with item deadlines; confidence ratings; and pain intensity ratings. Using this package, item response theory (IRT) models suitable for bounded continuous item scores can be fitted to data within a Bayesian framework. The package draws on posterior sampling facilities provided by R-package 'rstan' (Stan Development Team, 2025). Available models include the Beta IRT model by Noel and Dauvier (2007), the continuous response model by Samejima (1973), the unbounded normal model by Mellenbergh (1994), and the Simplex IRT model by Flores et al. (2020). All models can be fitted with or without zero-one inflation (Molenaar et al., 2022). Model fit comparisons can be conducted using the Watanabe–Akaike information criterion (WAIC), the leave-one-out cross-validation information criterion (LOOIC), and the fully marginalized likelihood (i.e., Bayes factors).

Author(s)

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References

- Flores, S., Bazan, J.L., & Bolfarine, H. (2020). A hierarchical joint model for bounded response time and response accuracy. In M. Wiberg, D. Molenaar, J. González, U. Bockenholt, & K. S. Kim (Eds.), *Quantitative psychology: The 84th Annual Meeting of the Psychometric Society, Santiago de Chile, Chile* (pp. 95-109). Springer. doi:10.1007/9783030434694_8
- Mellenbergh, G. J. (1994). A unidimensional latent trait model for continuous item responses. *Multivariate Behavioral Research*, **29**(3), 223-236. doi:10.1207/s15327906mbr2903_2
- Molenaar, D., Cúri, M., & Bazán, J.L. (2022). Zero and One Inflated Item Response Theory Models for Bounded Continuous Data. *Journal of Educational and Behavioral Statistics*, **47**, 693-735. doi:10.3102/10769986221108455
- Noel, Y., & Dauvier, B. (2007). A beta item response model for continuous bounded responses. *Applied Psychological Measurement*, **31**(1), 47-73. doi:10.1177/0146621605287691
- Samejima, F. (1973). Homogeneous case of the continuous response model. *Psychometrika*, **38**(2), 203-219. doi:10.1007/BF02291114
- Stan Development Team (2025). RStan: the R interface to Stan. R package version 2.32.7. <https://mc-stan.org/>

Abasement

Abasement data

Description

Bounded continuous items responses of 244 subjects to the 10 items from the Abasement subscale of the Adjectives Check List (ACL; Gough & Heilbrun, 1980) including the covariate female which is code 0 and 1

Format

The item scores have originally been scored on a 60 millimeter line segment on which the subjects had to indicate to what degree each adjective applies to them. These scores have been recoded into a [0,1] interval. The Abasement scale does not contain 1 scores but it does contain 0 scores. All subscales of the ACL including the Abasement scale have been analyzed using bounded continuous IRT models with zero-one inflation by Molenaar et al. (2022; see Table 10 for the model fit statistics of all ACL subscales and see Table 11 for the parameter estimates of the Abasement scale). The covariate female needs to be loaded separately but subjects are in the same order so that data can be cbind-ed if needed.

References

Gough, H. G., & Heilbrun, A. B. (1980). *The adjective check list, manual 1980 Edition*. Consulting Psychologists Press.

Molenaar, D., Cúri, M., & Bazán, J.L. (2022). Zero and One Inflated Item Response Theory Models for Bounded Continuous Data. *Journal of Educational and Behavioral Statistics*, **47**, 693-735. doi:10.3102/10769986221108455

See Also

`fitBIRT` to estimate various bounded continuous IRT models to data.

`plot.BoundIRT` to plot the item and test information curves and predicted densities for the different models.

`coef.BoundIRT` to extract item parameter estimates from a BoundIRT object.

`bridgeBIRT` to use bridge sampling to calculate the marginal loglikelihood for a model in a BoundIRT object.

`latregBIRT` to conduct a latent regression of the person parameters on some observed predictor variables.

`rBIRT` simulate data according to a (zero/one inflated) bounded IRT model.

Examples

```
data(Abasement)
data(female)
```

```
bridgeBIRT
```

Estimate fully marginalized log-likelihood using bridge sampling.

Description

This function uses bridge sampling as discussed by Gronau et al. (2017) to obtain the fully marginalized likelihood of an estimated bounded IRT model.

Usage

```
bridgeBIRT(object, niter=10000, tol=1e-7, silent=FALSE)
```

Arguments

<code>object</code>	A BoundIRT-object.
<code>niter</code>	Number of iterations of the algorithm.
<code>tol</code>	Tolerance for the algorithm. Algorithm stops if the change in $\log(r_1)$ between subsequent iterations is smaller than this value, see Details .
<code>silent</code>	If TRUE no progress is displayed during estimation.

Details

In bridge sampling, a so-called bridge function is used to estimate the fully marginalized likelihood by combining existing posterior samples with additional samples drawn from a proposal distribution. In bridgeBIRT, a multivariate normal proposal distribution is used. Using these proposal samples, the final expression for the marginal likelihood involves an iterative procedure (see Equation 4.1 from Meng & Wong, 1996) which stops if the change in marginal likelihood between iterations does not exceed the tolerance.

To improve numerical stability and avoid overflow in the `exp()` function, we follow the approach described in Appendix B of Gronau et al. (2017). Specifically, the median log-likelihood value, l^* , is subtracted from the log-marginal likelihood, and only the remaining component, r_1 , is estimated. After the iterative scheme has converged, these two components are recombined to obtain the final estimate of the marginal likelihood.

Value

A list containing:

<code>log_ml</code>	The fully marginalized log-likelihood.
<code>r1</code>	The estimate of r_1 .
<code>l_start</code>	The value of l^* used (median log-likelihood across posterior samples).

Author(s)

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References

- Gronau, Q. F., et al. (2017). A tutorial on bridge sampling. *Journal of mathematical psychology*, **81**, 80-97. doi:10.1016/j.jmp.2017.09.005
- Meng, X. L., & Wong, W. H. (1996). Simulating ratios of normalizing constants via a simple identity: a theoretical exploration. *Statistica Sinica*, **6**, 831-860. <https://www.jstor.org/stable/24306045>

See Also

[fitBIRT](#) to estimate various bounded continuous IRT models to data.

[plot.BoundIRT](#) to plot the item and test information curves and predicted densities for the different models.

[coef.BoundIRT](#) to extract item parameter estimates from a BoundIRT object.

[latregBIRT](#) to conduct a latent regression of the person parameters on some observed predictor variables.

[rBIRT](#) simulate data according to a (zero/one inflated) bounded IRT model.

Examples

```
# read in the pre-estimated object containing the Abasement results
# for the Beta IRT model and estimate the marginal likelihood

data(out_beta)
bridgeBIRT(out_beta)
```

coef.BoundIRT	<i>Obtain item parameter estimates</i>
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Description

Extracts a matrix of posterior means for the item parameters of a BoundIRT-object

Usage

```
## S3 method for class 'BoundIRT'
coef(object, sd=FALSE, ...)
```

Arguments

object	A BoundIRT-object.
sd	A Boolean indicating if posterior standard deviations should be returned as well
...	Other arguments to be passed to print()

Value

A matrix containing the posterior mean (and standard deviations if sd=TRUE) of the item parameters from a bounded IRT model fit with the fitBIRT() function.

Author(s)

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See Also

[fitBIRT](#) to estimate various bounded continuous IRT models to data.

[plot.BoundIRT](#) to plot the item and test information curves and predicted densities for the different models.

[coef.BoundIRT](#) to extract item parameter estimates from a BoundIRT object.

[bridgeBIRT](#) to use bridge sampling to calculate the marginal loglikelihood for a model in a BoundIRT object.

`latregBIRT` to conduct a latent regression of the person parameters on some observed predictor variables.

`rBIRT` simulate data according to a (zero and/or one inflated) bounded IRT model.

Examples

```
# read in the pre-estimated object containing the Abasement results
data(out_beta)

coef(out_beta)
```

fitBIRT

Fit various IRT models for bounded continuous items to data

Description

This function fits various IRT models for bounded continuous items using MCMC sampling in R-package 'rstan' (Stan Development Team, 2025). Available models include the Beta IRT model by Noel and Dauvier (2007), the continuous response model by Samejima (1973), the unbounded normal model by Mellenbergh (1994), and the Simplex IRT model by Flores et al. (2020). All models can be fitted with or without a zero and/or one inflation (Molenaar et al., 2022).

Usage

```
fitBIRT(z,
        model=c("beta", "samejima", "simplex", "normal"),
        inflated=c("auto", "zero", "one", "both", "none"),
        iter=2000,
        warmup=NULL,
        nchains=1,
        prior=NULL,
        silent=FALSE,
        ...)
```

Arguments

<code>z</code>	A matrix of size N by n containing the bounded continuous item scores, where N is the number of subjects and n is the number of items. The items should be coded in a $(0, 1)$, a $[0, 1)$, a $(0, 1]$, or $[0, 1]$ interval.
<code>model</code>	A character string indicating the model to be fit. The options are: "beta" (Default) The Beta IRT model by Noel and Dauvier (2007) with item specific discrimination parameter. "samejima" The IRT model by Samejima (1973). "simplex" The Simplex IRT model by Flores et al. (2020).

	"normal" The (unbounded) unidimensional normal linear factor model by Meltenbergh (1994)
inflated	A character string indicating the kind of inflation to use. The options are: "auto" (Default) Zero and one inflation parameters are only added for items that actually contain zero and/or one scores . "zero" Zero inflation parameters are estimated for all items. "one" One inflation parameters are estimated for all items. "both" Zero and one inflation parameters are estimated for all items. "none" No zero-one inflation. The data shouldn't contain 0 or 1 scores.
iter	Number of MCMC samples to draw, including warmup samples
warmup	Number of warmup samples. Default is floor(iter/2)
nchains	Number of MCMC chains to use. Default is 1.
prior	If NULL, the default priors are being used. Otherwise a list can be specified giving the prior standard deviation of (some of) the parameters. See Details
silent	If TRUE no details are displayed during estimation
...	Additional arguments to pass to <code>rstan::sampling()</code>

Details

Function fitBIRT fits the models discussed by Molenaar et al. (2022) including the facilities for zero and/or one inflation. If α_i , β_i , and ϕ_i are respectively the discrimination, easiness, and dispersion parameters of item i , θ_p is the latent variable position of subject p , and z_{pi} is the bounded continuous item score of subject p on item i , then the different models can be given as follows:

Beta model $z_{pi} \sim \text{Beta}(a_{pi}, b_{pi})$

$$a_{pi} = \exp(.5(\alpha_i \theta_p + \beta_i + \log(\phi_i)))$$

$$b_{pi} = \exp(.5(-\alpha_i \theta_p - \beta_i + \log(\phi_i)))$$

Samejima model $z'_{pi} \sim \text{Normal}(\alpha_i \theta_p + \beta_i, \phi_i)$

$$z'_{pi} = \text{logit}(z_{pi})$$

Simplex model $z_{pi} \sim \text{Simplex}(1/(1 + \exp(-(\alpha_i \theta_p + \beta_i))), \phi_i)$

Normal model $z_{pi} \sim \text{Normal}(\alpha_i \theta_p + \beta_i, \phi_i)$

Zero and/or one inflation To these models, zero and/or one inflation can be added as follows:

$$A = P(z_{pi} = 0 | \theta_p) = 1/(1 + \exp(-(\gamma_{0i} - \alpha_i \theta_p)))$$

$$B = P(z_{pi} = 1 | \theta_p) = 1 - 1/(1 + \exp(-(\gamma_{1i} - \alpha_i \theta_p)))$$

where γ_{0i} and γ_{1i} model the amount of zero and one inflation respectively. The conventional models above are accommodated as follows:

$$f(z_{pi} | \theta_p) = A \text{ for } z_{pi} = 0$$

$$f(z_{pi} | \theta_p) = B \text{ for } z_{pi} = 1$$

$$f(z_{pi} | \theta_p) = [(1 - B) - A] \times k(z_{pi} | \theta_p) \text{ for } z_{pi} \in (0, 1)$$

where $k(\cdot)$ is the distribution according to the conventional model above. See Molenaar et al. (2022) for details.

In estimating the models above, normal priors are specified for θ_p , $\log(\alpha_i)$, β_i , $\log(\phi_i)$, γ_{0i} , and γ_{1i} . All priors have mean 0, and by default, a standard deviation of 1 for θ_p (for identification purposes) and 10 for the other parameters. Changing (one of) the defaults involves specifying a list with elements sT, sA, sB, sP and/or sG, which overrides the default. It is thus possible to stick to the defaults, but change the prior standard deviation for $\log \alpha_i$ and β_i by using for instance `prior=list(sA=5, sB=5)`. Note that setting sG affects both the prior of γ_{0i} and γ_{1i} .

Value

An object of class BoundIRT with values:

output	The posterior means and standard deviations of the item parameters.
theta	The posterior means and standard deviations of the person parameters.
mcmc	The stanfit object containing all sampling results. See stanfit .
prior	The prior standard deviations used in the list format discussed above.

For the BoundIRT object, the following methods are available:

summary.BoundIRT	which gives the default rstan summary overview of the parameters.
plot.BoundIRT	which provides various IRT plotting facilities, see plot.BoundIRT
print.BoundIRT	which gives the posterior means and standard deviations of the item parameters.
coef.BoundIRT	which returns the posterior means of the item parameters, see coef.BoundIRT .

Author(s)

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References

- Flores, S., Bazan, J.L., & Bolfarine, H. (2020). A hierarchical joint model for bounded response time and response accuracy. In M. Wiberg, D. Molenaar, J. González, U. Bockenholt, & K. S. Kim (Eds.), *Quantitative psychology: The 84th Annual Meeting of the Psychometric Society, Santiago de Chile, Chile* (pp. 95-109). Springer. doi:10.1007/9783030434694_8
- Mellenbergh, G. J. (1994). A unidimensional latent trait model for continuous item responses. *Multivariate Behavioral Research*, **29**(3), 223-236. doi:10.1207/s15327906mbr2903_2
- Molenaar, D., Cúri, M., & Bazán, J.L. (2022). Zero and One Inflated Item Response Theory Models for Bounded Continuous Data. *Journal of Educational and Behavioral Statistics*, **47**, 693-735. doi:10.3102/10769986221108455
- Noel, Y., & Dauvier, B. (2007). A beta item response model for continuous bounded responses. *Applied Psychological Measurement*, **31**(1), 47-73. doi:10.1177/0146621605287691
- Samejima, F. (1973). Homogeneous case of the continuous response model. *Psychometrika*, **38**(2), 203-219. doi:10.1007/BF02291114
- Stan Development Team (2025). RStan: the R interface to Stan. R package version 2.32.7. <https://mc-stan.org/>

See Also

`plot.BoundIRT` to plot the item and test information curves and predicted densities for the different models.

`coef.BoundIRT` to extract item parameter estimates from a BoundIRT object.

`loglikBIRT` to calculate the log-likelihood for each person and each posterior sample. Needed to calculate WAIC and LOOIC for a given model.

`repBIRT` to simulate replicated datasets using (a subset of) the posterior parameter samples. For posterior predictive model checking.

`bridgeBIRT` to use bridge sampling to calculate the marginal loglikelihood for a model in a BoundIRT object.

`latregBIRT` to conduct a latent regression of the person parameters on some observed predictor variables.

`rBIRT` simulate data according to a (zero/one inflated) bounded IRT model.

Examples

```
#load the Abasement data which contains zero inflation
data(Abasement)

# fit a zero inflated beta IRT model
# for illustrative purposes, we only use 20 iterations.
# In practice use many more!

res=fitBIRT(Abasement,model="beta",iter=20)
print(res) # quick overview
coef(res) # extract posterior item parameter means
summary(res,c("alpha","beta")) # request the rstan summary
```

latregBIRT

Latent regression of the latent variable from a bounded IRT model on observed predictor variables

Description

This function takes a fitted BoundIRT object and subjects the posterior latent variable distribution to a linear regression model.

Usage

```
latregBIRT(formula, X, object, method=c("posterior","Croon"), nboot=1000)
```

Arguments

formula	A formula to specify the linear regression of the latent variable on the predictor variables in X. See Examples .
X	A matrix of predictor variables. The column names of the matrix should at least include the predictor names provided in formula. All other variables are ignored.
object	A BoundIRT object obtained with fitBIRT().
method	The method to conduct the latent regression. Default is "posterior" which uses the posterior latent variable draws. Other option is "Croon" and "CroonSE" which uses the correction by Croon (2002). See Details .
nboot	The number of bootstrap samples for method="Croon". See Details .

Details

By default (method="posterior"), latregBIRT fits a linear regression model to the posterior latent variable distribution from a bounded continuous IRT model:

$$\theta = \mathbf{x}\boldsymbol{\gamma} + \epsilon$$

where \mathbf{x} is a vector of predictors variables, $\boldsymbol{\gamma}$ is a vector of regression parameters, and ϵ is a vector of residuals. Using the existing draws from the posterior latent variable distribution, $\hat{\theta}$ in BoundIRT object, samples are drawn from the posterior of $\boldsymbol{\gamma}$ conditional on $\hat{\theta}$. This posterior is normal with its mean being equal to the least square estimate of $\boldsymbol{\gamma}$, and its variance equal to $V\sigma^2$ where V is the inverse of $\text{cov}(X)$, and σ^2 is the residual variance which is sampled from its scaled inverse-chi-square posterior distribution. Note that the posterior of the latent variable is misspecified with respect to the predictor variables. The posterior is however unbiased for the number of items approaching infinity. As most applications of (bounded continuous) IRT models typically involve a limited number of items, the posterior covariance matrix of the latent variable and the predictor variables is adjusted for the nonzero variance in the latent variable posterior. The correction is based on the two-step approach by Croon (2002) in which the factor scores from a linear factor model are estimated in step 1 and used in a regression model in step 2. As such, Croon's method is a statistically valid alternative to fitting the factor model and latent regression model simultaneously. Vermunt (2025) discusses how Croon's method can be generalized to models with heterogenous measurement error like IRT models. latregBIRT implements this idea by correcting the covariance matrix of the latent variable and the predictor variables for each posterior latent variable draw using the formula from Vermunt (2025). Next, a linear regression is fit to each sample as described above.

For method="Croon" the above correction is applied on the EAP latent variable scores. Drawback is that no standard deviation corrections are available. These are therefore bootstrapped using nboot resamples.

Value

output	A matrix containing the posterior means and standard deviations of the regression slopes for each predictor (if method="posterior") or the regression slope estimates with bootstrapped standard errors (if method="Croon").
samples	A matrix containing the samples from the posterior distribution of the regression parameter (if method="posterior") or the regression parameter estimates on the bootstrapped samples (if method="Croon").

Author(s)

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References

Croon, M. (2002). Using predicted latent scores in general latent structure models. In G. Marcoulides and I. Moustaki (Eds.), *Latent Variable and Latent Structure Models* (pp. 195-224). Lawrence Erlbaum.

Vermunt J.K. (2025). Stepwise estimation of latent variable models: An overview of approaches. *Statistical Modelling*, **25**(6),530-551. doi:10.1177/1471082X251355693

See Also

[fitBIRT](#) to estimate various bounded continuous IRT models to data.

[plot.BoundIRT](#) to plot the item and test information curves and predicted densities for the different models.

[coef.BoundIRT](#) to extract item parameter estimates from a BoundIRT object.

[loglikBIRT](#) to calculate the log-likelihood for each person and each posterior sample. Needed to calculate WAIC and LOOIC for a given model.

[bridgeBIRT](#) to use bridge sampling to calculate the marginal loglikelihood for a model in a BoundIRT object.

[rBIRT](#) simulate data according to a (zero/one inflated) bounded IRT model.

Examples

```
# open pre-estimated Beta IRT model on Abasement data (see ?Abasement)
data(out_beta)

# simulate a latent regression with 2 covariates

EAP=out_beta$theta[,1]
N=length(EAP)
age=.4*EAP+sqrt(1-.4^2)*rnorm(N)
ses=.3*EAP+sqrt(1-.3^2)*rnorm(N)

# conduct latent regression
predictors=cbind(age,ses)
latregBIRT(~age+ses,predictors,out_beta)
```

loglikBIRT

Calculate the log-likelihood values of each person for each posterior parameter sample

Description

To facilitate model fit checking (e.g., leave one out cross-validation, WAIC), this function can be used to calculate the log-likelihood values of each person for each posterior parameter sample in a BoundIRT-object.

Usage

```
loglikBIRT(object, marginal=TRUE, nquad=15, silent=FALSE)
```

Arguments

object	A BoundIRT-object
marginal	If TRUE the marginal loglikelihood is calculated for each subject (default), otherwise the conditional likelihood is calculated for each subject-item combination. See Details .
nquad	If marginal=TRUE this argument determines the number of quadrature points used to approximate the integral in the marginal likelihood.
silent	If TRUE no details are displayed about the progress

Details

For latent variable models like the ones in BoundIRT, Merkle et al., (2019) recommend the use of the likelihood function that is marginalized over the persons parameters (i.e., not over the item parameters) in calculating fit statistics like the WAIC and LOOIC. Using marginal=TRUE will output this marginal likelihood value for each person and each sample of the posterior. If the interest is in calculating the conventional fit measures (e.g., conditional WAIC and DIC), marginal=FALSE should be used to obtain the likelihood values for each person conditional on the person and item parameters of each posterior sample.

Value

The function returns a matrix of dimensions (nsamples) by (N) containing the (marginal) log-likelihood values of the subjects for each posterior sample.

Author(s)

Dylan Molenaar <d.molenaar@uva.nl>

References

- Gabry J, Simpson D, Vehtari A, Betancourt M, Gelman A (2019). Visualization in Bayesian workflow. *Journal of the Royal Statistical Society, A*, **182**, 389-402. doi:10.1111/rssa.12378
- Merkle EC, Furr D, Rabe-Hesketh S. (2019). Bayesian Comparison of Latent Variable Models: Conditional Versus Marginal Likelihoods. *Psychometrika*, **84**(3), 802-829. doi:10.1007/s11336-019096790

See Also

`fitBIRT` to estimate various bounded continuous IRT models to data.

`plot.BoundsIRT` to plot the item and test information curves and predicted densities for the different models.

`coef.BoundsIRT` to extract item parameter estimates from a `BoundsIRT` object.

`repBIRT` to simulate replicated datasets using (a subset of) the posterior parameter samples. For posterior predictive model checking.

`bridgeBIRT` to use bridge sampling to calculate the marginal loglikelihood for a model in a `BoundsIRT` object.

`latregBIRT` to conduct a latent regression of the person parameters on some observed predictor variables.

Examples

```
#read in the prefitted results from the Abasement data (see ?Abasement and ?out_beta)
data(out_beta)

# Calculate marginal log-likelihood

logL=loglikBIRT(out_beta)

#logL can now be used for e.g., model fit assessment using loo() from R-package loo

#library loo should be available as it is part of rstan which is an import of BoundsIRT
if (requireNamespace("loo", quietly = TRUE)) {
  library(loo)
  loo(logL) # gives the marginal LOOIC
  waic(logL) # gives the marginal WAIC
}
```

out_beta

Estimation results of a Zero Inflated Beta IRT model fit to the Abasement data

Description

The object returned by `fitBIRT` containing the results of a zero inflated beta IRT model fit to the Abasement data of the Adjectives Check List (ACL; Gough & Heilbrun, 1980). The Abasement scale has been analyzed using a zero-one inflated beta IRT model by Molenaar et al. (2022). See Table 10 for the model fit statistics of all ACL subscales including the Abasement subscale and see Table 11 for the parameter estimates of the Abasement scale. Note that the estimates in `out_beta` and the subsequent model fit statistics obtained using `bridgeBIRT` are based on a zero inflated model only, therefore, results are slightly different.

Format

```
A BoundIRT object obtained using
set.seed(1310)
data(Abasement)
out_beta=fitBIRT(Abasement,model="beta")
```

References

Gough, H. G., & Heilbrun, A. B. (1980). *The adjective check list, manual 1980 Edition*. Consulting Psychologists Press.

Molenaar, D., Cúri, M., & Bazán, J.L. (2022). Zero and One Inflated Item Response Theory Models for Bounded Continuous Data. *Journal of Educational and Behavioral Statistics*, **47**, 693-735. doi:10.3102/10769986221108455

See Also

[fitBIRT](#) to estimate various bounded continuous IRT models to data.

[plot.BoundIRT](#) to plot the item and test information curves and predicted densities for the different models.

[coef.BoundIRT](#) to extract item parameter estimates from a BoundIRT object.

[loglikBIRT](#) to calculate the log-likelihood for each person and each posterior sample. Needed to calculate WAIC and LOOIC for a given model.

[repBIRT](#) to simulate replicated datasets using (a subset of) the posterior parameter samples. For posterior predictive model checking.

[bridgeBIRT](#) to use bridge sampling to calculate the marginal loglikelihood for a model in a BoundIRT object.

[latregBIRT](#) to conduct a latent regression of the person parameters on some observed predictor variables.

[rBIRT](#) simulate data according to a (zero/one inflated) bounded IRT model.

Examples

```
data(out_beta)
```

plot.BoundIRT

Plotting function for BoundIRT-objects.

Description

This function can be used to produce item and test information curves, and the model implied densities of a fitted bounded continuous IRT model.

Usage

```
## S3 method for class 'BoundIRT'
plot(x,
      what=c("icc","iic","tic","density"),
      items=NULL,
      separate=FALSE,
      range=c(-3,3),
      by=.001,
      ymax=NULL,
      xlab=NULL,
      ylab=NULL,
      main=NULL,
      col=NULL,
      lwd_prob=2,
      ...)
```

Arguments

x	A BoundIRT-object to produce the plots for.
what	A character string indicating what plot to produce. The options are: "icc" (Default) Item characteristic curves. "iic" Item information curves. "tic" Test information curves. "density" The model implied density for the observed data.
items	A numeric vector indicating which items to consider for the plots. If NULL all items are plotted (default). If items is provided and what="tic", the test information is based only on these items.
separate	If separate=TRUE the different items are depicted in separate plots
range	Range of the latent variable on the x-axis. Argument will be neglected for what="density".
by	increment for the x-axis of the plot.
ymax	Specify the maximum value for the y-axis. For multiple items, this can be an array of size length(items), or a single value for all items.
xlab	Specify an alternative label for the x-axis.
ylab	Specify an alternative label for the y-axis.
main	Specify an alternative title for plot.
col	The color code to be used for plotting different items. Can be an array and will be recycled if length(items)!=length(col). Argument can be any valid R color specification. Default is 1:6.
lwd_prob	For what="density" and a model with zero and/or one inflation, the probabilities of zero and one scores are depicted using vertical lines. The width of these lines can be set using this argument. Default is 2. Width of the other lines can be set using ... below.
...	Other arguments to be passed to matplot

Details

Plotting the model implied densities is relatively slow due to the numerical integration involved in marginalizing over the latent variable. In the presence of zero and/or one inflation, model implied densities include the probability of zero and/or one scores by a vertical line. As this vertical line represents a probability and the rest of the plot is about density, the zero/one probabilities may be masked if density values are large even if the zero/one inflation is quite substantial. See **Examples** how to extract the zero/one probabilities in the case these are hard to see from the plot.

Value

A matrix containing x-axis values (either the latent variable or the observed variable) and the y-axis values for each item.

Author(s)

Dylan Molenaar <d.molenaar@uva.nl>

See Also

[fitBIRT](#) to estimate various bounded continuous IRT models to data.

[coef.BoundIRT](#) to extract item parameter estimates from a BoundIRT object.

[loglikBIRT](#) to calculate the log-likelihood for each person and each posterior sample. Needed to calculate WAIC and LOOIC for a given model.

[repBIRT](#) to simulate replicated datasets using (a subset of) the posterior parameter samples. For posterior predictive model checking.

[bridgeBIRT](#) to use bridge sampling to calculate the marginal loglikelihood for a model in a BoundIRT object.

[latregBIRT](#) to conduct a latent regression of the person parameters on some observed predictor variables.

[rBIRT](#) simulate data according to a (zero/one inflated) bounded IRT model.

Examples

```
#load results for zero inflated beta IRT model fit to the Abasement data
# see ?Abasement and ?out_beta
data(out_beta)

# plots for item 1
oldpar=par(mfrow=c(2,2))
plot(out_beta,what="icc",items=1)
plot(out_beta,what="iic",items=1)
plot(out_beta,what="tic",items=1)
den_plot=plot(out_beta,what="density",items=1)
par(oldpar)

#extract zero probabilities (there are no ones in the Abasement data)
den_plot$out[1]      # zero probabilities
```

rBIRT	<i>Simulate data according to various IRT models for bounded continuous items</i>
-------	---

Description

This function simulates data according to various IRT models for bounded continuous items. Available models include the Beta IRT model by Noel and Dauvier (2007), the continuous response model by Samejima (1973), the unbounded normal model by Mellenbergh (1994), and the Simplex IRT model by Flores et al. (2020). All models can be simulated with or without zero and/or one inflation (Molenaar et al., 2022).

Usage

```
rBIRT(N,nit,alpha,beta,phi,theta,
      gamma0=NULL,
      gamma1=NULL,
      model=c("beta","samejima","simplex","normal"))
```

Arguments

N	Number of subjects
nit	Number of items
alpha	A nit-dimensional array of true discrimination parameter values
beta	A nit-dimensional array of true easiness parameter values
phi	A nit-dimensional array of true dispersion parameter values
theta	A N-dimensional array of true person parameter values
gamma0	Optional: A nit-dimensional array of true zero inflation parameters
gamma1	Optional: A nit-dimensional array of true one inflation parameters
model	A character string indicating what model to use to simulate the data. The options are: "beta" (Default) The Beta IRT model by Noel and Dauvier (2007) with item specific discrimination parameter. "samejima" The IRT model by Samejima (1973). "simplex" The Simplex IRT model by Flores et al. (2020). "normal" The (unbounded) unidimensional normal linear factor model by Mellenbergh (1994)

Details

If arguments `gamma0` and `gamma1` are not provided, data is simulated according to the conventional models. Zero and one inflation can be introduced separately by only providing `gamma0` or `gamma1`, or zero and one inflation can both be introduced by specifying both `gamma0` and `gamma1`. If the interest is in simulating some -but not all- items with zero and/or one inflation, the uninflated items can be coded as `-Inf` in `gamma0` and `Inf` in `gamma1`. See [fitBIRT](#) for the exact parameterization of the models.

Value

A matrix of size `N` by `nit` containing the simulated item responses.

Author(s)

Dylan Molenaar <d.molenaar@uva.nl>

References

Flores, S., Bazan, J.L., & Bolfarine, H. (2020). A hierarchical joint model for bounded response time and response accuracy. In M. Wiberg, D. Molenaar, J. González, U. Bockenholt, & K. S. Kim (Eds.), *Quantitative psychology: The 84th Annual Meeting of the Psychometric Society, Santiago de Chile, Chile* (pp. 95-109). Springer. doi:10.1007/9783030434694_8

Mellenbergh, G. J. (1994). A unidimensional latent trait model for continuous item responses. *Multivariate Behavioral Research*, **29**(3), 223-236. doi:10.1207/s15327906mbr2903_2

Molenaar, D., Cúri, M., & Bazán, J.L. (2022). Zero and One Inflated Item Response Theory Models for Bounded Continuous Data. *Journal of Educational and Behavioral Statistics*, **47**, 693-735. doi:10.3102/10769986221108455

Noel, Y., & Dauvier, B. (2007). A beta item response model for continuous bounded responses. *Applied Psychological Measurement*, **31**(1), 47-73. doi:10.1177/0146621605287691

Samejima, F. (1973). Homogeneous case of the continuous response model. *Psychometrika*, **38**(2), 203-219. doi:10.1007/BF02291114

Stan Development Team (2025). RStan: the R interface to Stan. R package version 2.32.7. <https://mc-stan.org/>

See Also

[fitBIRT](#) to estimate various bounded continuous IRT models to data.

[plot.BoundIRT](#) to plot the item and test information curves and predicted densities for the different models.

[coef.BoundIRT](#) to extract item parameter estimates from a BoundIRT object.

[loglikBIRT](#) to calculate the log-likelihood for each person and each posterior sample. Needed to calculate WAIC and LOOIC for a given model.

[repBIRT](#) to simulate replicated datasets using (a subset of) the posterior parameter samples. For posterior predictive model checking.

[bridgeBIRT](#) to use bridge sampling to calculate the marginal loglikelihood for a model in a BoundIRT object.

`latregBIRT` to conduct a latent regression of the person parameters on some observed predictor variables.

Examples

```
# data sim with 100 subjects and 10 items according to
# beta IRT model with zero and one inflation

nit=10
N=100
beta=runif(nit, .5,1)
alpha=runif(nit, .5, .7)
gamma0=runif(nit, -3, -1.5)
gamma1=runif(nit, 1.5, 3)

theta=rnorm(N)

phi=seq(1.5, 2.5, length=nit)
z=rBIRT(N, nit, alpha, beta, phi, theta, gamma0, gamma1, model="beta")
```

repBIRT

Simulate replicated datasets using the posterior parameter samples from a BoundIRT-object

Description

To facilitate posterior predictive model checking, this function can be used to simulate replicated datasets for each of the samples from the posterior parameter distribution in a BoundIRT-object.

Usage

```
repBIRT(object, nrep=1000, silent=FALSE)
```

Arguments

<code>object</code>	A BoundIRT-object
<code>nrep</code>	Number of replicated datasets to produce. See Details .
<code>silent</code>	If TRUE no details are displayed about the progress

Details

`repBIRT` is a wrapper around `rBIRT` extracting the posterior parameter samples, and simulating data for a subset of the samples. That is, for many posterior predictive purposes, not all posterior parameter samples are needed. Therefore, only the last `nrep` samples will be used. Setting `nrep` to be equal to the total number of posterior samples will use all of them.

Value

An array of size nrep by N by nit containing the replicated datasets.

Author(s)

Dylan Molenaar <d.molenaar@uva.nl>

References

Gabry J, Simpson D, Vehtari A, Betancourt M, Gelman A (2019). Visualization in Bayesian workflow. *Journal of the Royal Statistical Society, A*, **182**, 389-402. doi:10.1111/rssa.12378

See Also

[fitBIRT](#) to estimate various bounded continuous IRT models to data.

[plot.BoundIRT](#) to plot the item and test information curves and predicted densities for the different models.

[coef.BoundIRT](#) to extract item parameter estimates from a BoundIRT object.

[loglikBIRT](#) to calculate the log-likelihood for each person and each posterior sample. Needed to calculate WAIC and LOOIC for a given model.

[bridgeBIRT](#) to use bridge sampling to calculate the marginal loglikelihood for a model in a BoundIRT object.

[latregBIRT](#) to conduct a latent regression of the person parameters on some observed predictor variables.

Examples

```
#load the Abasement data and fitting results for the Beta IRT model
data(Abasement)
data(out_beta)

#generate 10 replicated datasets
z_rep=repBIRT(out_beta,nrep=10)

#these can be used for e.g., posterior predictive checks
#using the suggested bayesplot library
if (requireNamespace("bayesplot", quietly = TRUE)) {
  bayesplot::ppc_dens_overlay(Abasement[,1],z_rep[, ,1]) #for item 1
  bayesplot::ppc_dens_overlay(Abasement[,1],z_rep[, ,2]) #for item 2, etc.
}
```

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