

Package: ProbBreed (via r-universe)

August 28, 2024

Title Probability Theory for Selecting Candidates in Plant Breeding

Version 1.0.4.2

Description Use probability theory under the Bayesian framework for calculating the risk of selecting candidates in a multi-environment context. Contained are functions used to fit a Bayesian multi-environment model (based on the available presets), extract posterior values and maximum posterior values, compute the variance components, check the model's convergence, and calculate the probabilities. For both across and within-environments scopes, the package computes the probability of superior performance and the pairwise probability of superior performance. Furthermore, the probability of superior stability and the pairwise probability of superior stability across environments is estimated. A joint probability of superior performance and stability is also provided.

URL <https://github.com/saulo-chaves/ProbBreed>,
https://saulo-chaves.github.io/ProbBreed_site/,
<https://saulo-chaves.github.io/ProbBreed/>

BugReports <https://github.com/saulo-chaves/ProbBreed/issues>

License AGPL (>= 3)

Depends R (>= 3.5.0)

Imports ggplot2, lifecycle, methods, Rcpp (>= 0.12.0), RcppParallel (>= 5.0.1), rlang, rstan (>= 2.32.0), rstantools (>= 2.4.0), stats, utils

LinkingTo StanHeaders (>= 2.32.0), rstan (>= 2.32.0), BH (>= 1.72.0-2), Rcpp (>= 0.12.0), RcppEigen (>= 0.3.3.3.0), RcppParallel (>= 5.0.1)

Suggests knitr, rmarkdown

Encoding UTF-8

UseLTO true

NeedsCompilation yes
Roxygen list(markdown = TRUE)
RoxygenNote 7.3.2
LazyData true
Biarch true
SystemRequirements GNU make
Repository <https://saulo-chaves.r-universe.dev>
RemoteUrl <https://github.com/saulo-chaves/probbreed>
RemoteRef HEAD
RemoteSha 586894da6fbe0f62e4d5fed48939e9e16daf368f

Contents

bayes_met	2
extr_outs	6
maize	7
plot.extr	8
plot.probsup	9
print.extr	11
print.probsup	12
prob_sup	12
soy	16
Index	17

bayes_met	<i>Bayesian model for multi-environment trials</i>
-----------	--

Description

Fits a Bayesian multi-environment model using `rstan`, the R interface to Stan.

Usage

```
bayes_met(  
  data,  
  gen,  
  loc,  
  repl,  
  trait,  
  reg = NULL,  
  year = NULL,  
  res.het = FALSE,  
  iter = 2000,
```

```

cores = 1,
chains = 4,
pars = NA,
warmup = floor(iter/2),
thin = 1,
seed = sample.int(.Machine$integer.max, 1),
init = "random",
verbose = FALSE,
algorithm = c("NUTS", "HMC", "Fixed_param"),
control = NULL,
include = TRUE,
show_messages = TRUE,
...
)

```

Arguments

<code>data</code>	A data frame in which to interpret the variables declared in the other arguments.
<code>gen, loc</code>	A string. The name of the columns that contain the evaluated candidates and locations (or environments, if you are working with factor combinations), respectively.
<code>repl</code>	A string, a vector, or NULL. If the trial is randomized in complete blocks design, <code>repl</code> will be a string representing the name of the column that corresponds to the blocks. If the trial is randomized in incomplete blocks design, <code>repl</code> will be a string vector containing the name of the columns that correspond to the replicate and block effects on the first and second positions, respectively (<code>c(replicate, block)</code>). If the data does not have replicates, <code>repl</code> will be NULL.
<code>trait</code>	A string. The analysed variable. Currently, only single-trait models are fitted.
<code>reg</code>	A string or NULL. The name of the column that contain information on regions or mega-environments. NULL (default) if not applicable.
<code>year</code>	A string or NULL. The name of the column that contain information on years (or seasons). NULL (default) if not applicable.
<code>res.het</code>	Should the model consider heterogeneous residual variances? Defaults for FALSE. If TRUE, the model will estimate one residual variance per location (or environment). If <code>repl = NULL</code> , <code>res.het</code> must be TRUE.
<code>iter</code>	A positive integer specifying the number of iterations for each chain (including warmup). The default is 2000.
<code>cores</code>	Number of cores to use when executing the chains in parallel, which defaults to 1 but we recommend setting the <code>mc.cores</code> option to be as many processors as the hardware and RAM allow (up to the number of chains).
<code>chains</code>	A positive integer specifying the number of Markov chains. The default is 4.
<code>pars</code>	A vector of character strings specifying parameters of interest. The default is NA indicating all parameters in the model. If <code>include = TRUE</code> , only samples for parameters named in <code>pars</code> are stored in the fitted results. Conversely, if <code>include = FALSE</code> , samples for all parameters <i>except</i> those named in <code>pars</code> are stored in the fitted results.

warmup	A positive integer specifying the number of warmup (aka burnin) iterations per chain. If step-size adaptation is on (which it is by default), this also controls the number of iterations for which adaptation is run (and hence these warmup samples should not be used for inference). The number of warmup iterations should be smaller than <code>iter</code> and the default is <code>iter/2</code> .
thin	A positive integer specifying the period for saving samples. The default is 1, which is usually the recommended value.
seed	The seed for random number generation. The default is generated from 1 to the maximum integer supported by R on the machine. Even if multiple chains are used, only one seed is needed, with other chains having seeds derived from that of the first chain to avoid dependent samples. When a seed is specified by a number, <code>as.integer</code> will be applied to it. If <code>as.integer</code> produces NA, the seed is generated randomly. The seed can also be specified as a character string of digits, such as "12345", which is converted to integer.
init	Initial values specification. See the detailed documentation for the <code>init</code> argument in stan .
verbose	TRUE or FALSE: flag indicating whether to print intermediate output from Stan on the console, which might be helpful for model debugging.
algorithm	One of sampling algorithms that are implemented in Stan. Current options are "NUTS" (No-U-Turn sampler, Hoffman and Gelman 2011, Betancourt 2017), "HMC" (static HMC), or "Fixed_param". The default and preferred algorithm is "NUTS".
control	A named list of parameters to control the sampler's behavior. See the details in the documentation for the <code>control</code> argument in stan .
include	Logical scalar defaulting to TRUE indicating whether to include or exclude the parameters given by the <code>pars</code> argument. If FALSE, only entire multidimensional parameters can be excluded, rather than particular elements of them.
show_messages	Either a logical scalar (defaulting to TRUE) indicating whether to print the summary of Informational Messages to the screen after a chain is finished or a character string naming a path where the summary is stored. Setting to FALSE is not recommended unless you are very sure that the model is correct up to numerical error.
...	Additional arguments can be <code>chain_id</code> , <code>init_r</code> , <code>test_grad</code> , <code>append_samples</code> , <code>refresh</code> , <code>enable_random_init</code> . See the documentation in stan .

Details

The function has nine available models, which will be fitted according to the options set in the arguments:

1. Entry-mean model : fitted when `rep1 = NULL`, `reg = NULL` and `year = NULL`:

$$y = \mu + g + l + \varepsilon$$

Where y is the phenotype, μ is the intercept, g is the genotypic effect, l is the location (or environment) effect, and ε is the residue (which contains the genotype-by-location interaction, in this case).

2. Randomized complete blocks design : fitted when repl is a single string. It will fit different models depending if reg and year are NULL:

- reg = NULL and year = NULL :

$$y = \mu + g + l + gl + r + \varepsilon$$

where gl is the genotype-by-location effect, and r is the replicate effect.

- reg = "reg" and year = NULL :

$$y = \mu + g + m + l + gl + gm + r + \varepsilon$$

where m is the region effect, and gm is the genotype-by-region effect.

- reg = NULL and year = "year" :

$$y = \mu + g + t + l + gl + gt + r + \varepsilon$$

where t is the year effect, and gt is the genotype-by-year effect.

- reg = "reg" and year = "year" :

$$y = \mu + g + m + t + l + gl + gm + gt + r + \varepsilon$$

3. Incomplete blocks design : fitted when repl is a string vector of size 2. It will fit different models depending if reg and year are NULL:

- reg = NULL and year = NULL :

$$y = \mu + g + l + gl + r + b + \varepsilon$$

where b is the block within replicates effect.

- reg = "reg" and year = NULL :

$$y = \mu + g + m + l + gl + gm + r + b + \varepsilon$$

- reg = NULL and year = "year" :

$$y = \mu + g + t + l + gl + gt + r + b + \varepsilon$$

- reg = "reg" and year = "year" :

$$y = \mu + g + m + t + l + gl + gm + gt + r + b + \varepsilon$$

The models described above have predefined priors:

$$x \sim \mathcal{N}(0, S^{[x]})$$

$$\sigma \sim \mathcal{H}\text{-}\downarrow\{\mathcal{C}\text{-}\square\} \langle \uparrow (0, S^{[\sigma]})$$

where x can be any effect but the error, and σ is the standard deviation of the likelihood. If `res.het = TRUE`, then $\sigma_k \sim \mathcal{H}\text{-}\downarrow\{\mathcal{C}\text{-}\square\} \langle \uparrow (0, S^{[\sigma_k]})$. The hyperpriors are set as follows:

$$S^{[x]} \sim \mathcal{H}\text{-}\downarrow\{\mathcal{C}\text{-}\square\} \langle \uparrow (0, \phi)$$

where ϕ is the known global hyperparameter defined such as $\phi = \max(y) \times 10$.

More details about the usage of `bayes_met` and other functions of the `ProbBreed` package can be found at https://saulo-chaves.github.io/ProbBreed_site/. Solutions to convergence or mixing issues can be found at <https://mc-stan.org/misc/warnings.html>.

Value

An object of S4 class `stanfit` representing the fitted results. Slot `mode` for this object indicates if the sampling is done or not.

Methods

`sampling` `signature(object = "stanmodel")` Call a sampler (NUTS, HMC, or Fixed_param depending on parameters) to draw samples from the model defined by S4 class `stanmodel` given the data, initial values, etc.

See Also

[rstan::sampling](#), [rstan::stan](#), [rstan::stanfit](#)

Examples

```
mod = bayes_met(data = maize,
                gen = "Hybrid",
                loc = "Location",
                repl = c("Rep", "Block"),
                trait = "GY",
                reg = "Region",
                year = NULL,
                res.het = TRUE,
                iter = 2000, cores = 2, chain = 4)
```

extr_outs

Extract outputs from stanfit objects obtained from [bayes_met](#)

Description

Extracts outputs of the Bayesian model fitted using [bayes_met\(\)](#), and provides some diagnostics.

Usage

```
extr_outs(model, probs = c(0.025, 0.975), verbose = FALSE)
```

Arguments

<code>model</code>	An object of class <code>stanfit</code> , obtained using bayes_met()
<code>probs</code>	A vector with two elements representing the probabilities (in decimal scale) that will be considered for computing the quantiles.
<code>verbose</code>	A logical value. If TRUE, the function will indicate the completed steps. Defaults to FALSE

Details

More details about the usage of `extr_outs` and other functions of the ProbBreed package can be found at https://saulo-chaves.github.io/ProbBreed_site/.

Value

The function returns an object of class `extr`, which is a list with:

- `variances` : a data frame containing the variance components of the model effects, their standard deviation, naive standard error and highest posterior density interval.
- `post` : a list with the posterior of the effects, and the data generated by the model.
- `map` : a list with the maximum posterior values of each effect
- `ppcheck` : a matrix containing the p-values of maximum, minimum, median, mean and standard deviation; effective number of parameters, WAIC2 value, Rhat and effective sample size.

See Also

[rstan::stan_diag](#), [ggplot2::ggplot](#), [rstan::check_hmc_diagnostics](#), [plot.extr](#)

Examples

```
mod = bayes_met(data = maize,
                gen = "Hybrid",
                loc = "Location",
                repl = c("Rep", "Block"),
                trait = "GY",
                reg = "Region",
                year = NULL,
                res.het = TRUE,
                iter = 2000, cores = 2, chain = 4)

outs = extr_outs(model = mod,
                 probs = c(0.05, 0.95),
                 verbose = TRUE)
```

maize

Maize real data set

Description

This dataset belongs to value of cultivation and use maize trials of Embrapa Maize and Sorghum, and was used by Dias et al. (2022). It contains the grain yield of 32 single-cross hybrids and four commercial checks (36 genotypes in total) evaluated in 16 locations across five regions or mega-environments. These trials were laid out in incomplete blocks design, using a block size of 6 and two replications per trial.

Usage

maize

Format

maize:
A data frame with 823 rows and 6 columns:
Location 16 locations
Region 5 regions
Rep 2 replicates
Block 6 blocks
Hybrid 36 genotypes
GY Grain yield (phenotypes)

Source

Dias, K. O. G, Santos J. P. R., Krause, M. D., Piepho H. -P., Guimarães, L. J. M., Pastina, M. M., and Garcia, A. A. F. (2022). Leveraging probability concepts for cultivar recommendation in multi-environment trials. *Theoretical and Applied Genetics*, 133(2):443-455. doi:10.1007/s0012202204041y

plot.extr	<i>Plots for the extr object</i>
-----------	----------------------------------

Description

Build plots using the outputs stored in the extr object.

Usage

```
## S3 method for class 'extr'  
plot(x, ..., category = "ppdensity")
```

Arguments

x	An object of class extr.
...	Passed to ggplot2::geom_histogram , when category = histogram. Useful to change the number of bins.
category	A string indicating which plot to build. See options in the Details section.

Details

The available options are:

- `ppdensity` : Density plots of the empirical and sampled data, useful to assess the model's convergence.
- `density` : Density plots of the model's effects.
- `histogram` : Histograms of the model's effects.
- `traceplot`: Trace plot showing the changes in the effects' values across iterations and chains.

See Also

[extr_outs](#)

Examples

```
mod = bayes_met(data = maize,
                gen = "Hybrid",
                loc = "Location",
                repl = c("Rep", "Block"),
                trait = "GY",
                reg = "Region",
                year = NULL,
                res.het = TRUE,
                iter = 2000, cores = 2, chain = 4)

outs = extr_outs(model = mod,
                 probs = c(0.05, 0.95),
                 verbose = TRUE)
plot(outs, category = "ppdensity")
plot(outs, category = "density")
plot(outs, category = "histogram")
plot(outs, category = "traceplot")
```

plot.probsup

Plots for the probsup object

Description

Build plots using the outputs stored in the probsup object.

Usage

```
## S3 method for class 'probsup'
plot(x, ..., category = "perfo", level = "across")
```

Arguments

<code>x</code>	An object of class <code>probsup</code> .
<code>...</code>	currently not used
<code>category</code>	A string indicating which plot to build. See options in the Details section.
<code>level</code>	A string indicating the information level to be used for building the plots. Options are "across" for focusing on the probabilities across environments, or "within" to focus on the within-environment effects. Defaults to "across".

Details

The available options are:

- `hpd` : a caterpillar plot representing the marginal genotypic value of each genotype, and their respective highest posterior density interval (95% represented by the thick line, and 97.5% represented by the thin line). Available only if `level = "across"`.
- `perfo` : if `level = "across"`, a lollipop plot illustrating the probabilities of superior performance. If `level = "within"`, a heatmap with the probabilities of superior performance within environments. If a model with `reg` and/or `year` is fitted, multiple plots are produced.
- `stabi`: a lollipop plot with the probabilities of superior stability. If a model with `reg` and/or `year` is fitted, multiple plots are produced. Available only if `level = "across"`. Unavailable if an entry-mean model was used in `bayes_met`.
- `pair_perfo` : if `level = "across"`, a heatmap representing the pairwise probability of superior performance (the probability of genotypes at the *x*-axis being superior. to those on the *y*-axis). If `level = "within"`, a list of heatmaps representing the pairwise probability of superior performance within environments. If a model with `reg` and/or `year` is fitted, multiple plots (and multiple lists) are produced. Should this option is set, it is mandatory to store the outputs in an object. (e.g., `pl <- plot(obj, category = "pair_perfo", level = "within")`) so they can be visualized one at a time. The option `level = "within"` is unavailable if an entry-mean model was used in `bayes_met`.
- `pair_stabi`: a heatmap with the pairwise probabilities of superior stability (the probability of genotypes at the *x*-axis being more stable than those on the *y*-axis). If a model with `reg` and/or `year` is fitted, multiple plots are produced. Available only if `level = "across"`. Unavailable if an entry-mean model was used in `bayes_met`.
- `joint`: a lollipop plot with the joint probabilities of superior performance and stability. Unavailable if an entry-mean model was used in `bayes_met`.

See Also

[prob_sup](#)

Examples

```
mod = bayes_met(data = maize,
               gen = "Hybrid",
               loc = "Location",
               repl = c("Rep", "Block"),
               trait = "GY",
```

```

      reg = "Region",
      year = NULL,
      res.het = TRUE,
      iter = 2000, cores = 2, chain = 4)

outs = extr_outs(model = mod,
  probs = c(0.05, 0.95),
  verbose = TRUE)

results = prob_sup(extr = outs,
  int = .2,
  increase = TRUE,
  save.df = FALSE,
  verbose = FALSE)

plot(results, category = "hpd")
plot(results, category = "perfo", level = "across")
plot(results, category = "perfo", level = "within")
plot(results, category = "stabi")
plot(results, category = "pair_perfo", level = "across")
plwithin = plot(results, category = "pair_perfo", level = "within")
plot(results, category = "pair_stabi")
plot(results, category = "joint")

```

print.extr	<i>Print an object of class extr</i>
------------	--------------------------------------

Description

Print a extr object in R console

Usage

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

Arguments

x	An object of class extr
...	currently not used

See Also

[extr_outs](#)

print.probsup	<i>Print an object of class probsup</i>
---------------	---

Description

Print a probsup object in R console

Usage

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

Arguments

x	An object of class probsup
...	currently not used

See Also

[prob_sup](#)

prob_sup	<i>Probabilities of superior performance and stability</i>
----------	--

Description

This function estimates the probabilities of superior performance and stability across environments, and probabilities of superior performance within environments.

Usage

```
prob_sup(extr, int, increase = TRUE, save.df = FALSE, verbose = FALSE)
```

Arguments

extr	An object of class extr, obtained from the extr_outs function
int	A numeric representing the selection intensity (between 0 and 1)
increase	Logical.TRUE (default) if the selection is for increasing the trait value, FALSE otherwise.
save.df	Logical. Should the data frames be saved in the work directory? TRUE for saving, FALSE (default) otherwise.
verbose	A logical value. If TRUE, the function will indicate the completed steps. Defaults to FALSE.

Details

Probabilities provide the risk of recommending a selection candidate for a target population of environments or for a specific environment. `prob_sup` computes the probabilities of superior performance and the probabilities of superior stability:

- Probability of superior performance

Let Ω represent the subset of selected genotypes based on their performance across environments. A given genotype j will belong to Ω if its genotypic marginal value (\hat{g}_j) is high or low enough compared to its peers. `prob_sup` leverages the Monte Carlo discretized sampling from the posterior distribution to emulate the occurrence of S trials. Then, the probability of the j^{th} genotype belonging to Ω is the ratio of success ($\hat{g}_j \in \Omega$) events and the total number of sampled events, as follows:

$$Pr(\hat{g}_j \in \Omega|y) = \frac{1}{S} \sum_{s=1}^S I(\hat{g}_j^{(s)} \in \Omega|y)$$

where S is the total number of samples ($s = 1, 2, \dots, S$), and $I(\hat{g}_j^{(s)} \in \Omega|y)$ is an indicator variable that can assume two values: (1) if $\hat{g}_j^{(s)} \in \Omega$ in the s^{th} sample, and (0) otherwise. S is conditioned to the number of iterations and chains previously set at [bayes_met](#).

Similarly, the within-environment probability of superior performance can be applied to individual environments. Let Ω_k represent the subset of superior genotypes in the k^{th} environment, so that the probability of the $j^{th} \in \Omega_k$ can be calculated as follows:

$$Pr(\hat{g}_{jk} \in \Omega_k|y) = \frac{1}{S} \sum_{s=1}^S I(\hat{g}_{jk}^{(s)} \in \Omega_k|y)$$

where $I(\hat{g}_{jk}^{(s)} \in \Omega_k|y)$ is an indicator variable mapping success (1) if $\hat{g}_{jk}^{(s)}$ exists in Ω_k , and failure (0) otherwise, and $\hat{g}_{jk}^{(s)} = \hat{g}_j^{(s)} + \hat{g}_{jk}^{(s)}$. Note that when computing within-environment probabilities, we are accounting for the interaction of the j^{th} genotype with the k^{th} environment.

The pairwise probabilities of superior performance can also be calculated across or within environments. This metric assesses the probability of the j^{th} genotype being superior to another experimental genotype or a commercial check. The calculations are as follows, across and within environments, respectively:

$$Pr(\hat{g}_j > \hat{g}_{j'}|y) = \frac{1}{S} \sum_{s=1}^S I(\hat{g}_j^{(s)} > \hat{g}_{j'}^{(s)}|y)$$

or

$$Pr(\hat{g}_{jk} > \hat{g}_{j'k}|y) = \frac{1}{S} \sum_{s=1}^S I(\hat{g}_{jk}^{(s)} > \hat{g}_{j'k}^{(s)}|y)$$

These equations are set for when the selection direction is positive. If `increase = FALSE`, $>$ is simply switched by $<$.

- Probability of superior stability

This probability makes a direct analogy with the method of Shukla (1972): a stable genotype is the one that has a low genotype-by-environment interaction variance $[var(\hat{ge})]$. Using the same probability principles previously described, the probability of superior stability is given as follows:

$$Pr [var (\hat{ge}_{jk}) \in \Omega | y] = \frac{1}{S} \sum_{s=1}^S I [var (\hat{ge}_{jk}^{(s)}) \in \Omega | y]$$

where $I [var (\hat{ge}_{jk}^{(s)}) \in \Omega | y]$ indicates if $var (\hat{ge}_{jk}^{(s)})$ exists in Ω (1) or not (0). Pairwise probabilities of superior stability are also possible in this context:

$$Pr [var (\hat{ge}_{jk}) < var (\hat{ge}_{j'k}) | y] = \frac{1}{S} \sum_{s=1}^S I [var (\hat{ge}_{jk}^{(s)}) < var (\hat{ge}_{j'k}^{(s)}) | y]$$

Note that j will be superior to j' if it has a **lower** variance of the genotype-by-environment interaction effect. This is true regardless if increase is set to TRUE or FALSE.

The joint probability independent events is the product of the individual probabilities. The estimated genotypic main effects and the variances of GEI effects are independent by design, thus the joint probability of superior performance and stability as follows:

$$Pr [\hat{g}_j \in \Omega \cap var (\hat{ge}_{jk}) \in \Omega] = Pr (\hat{g}_j \in \Omega) \times Pr [var (\hat{ge}_{jk}) \in \Omega]$$

The estimation of these probabilities are strictly related to some key questions that constantly arises in plant breeding:

- **What is the risk of recommending a selection candidate for a target population of environments?**
- **What is the probability of a given selection candidate having good performance if recommended to a target population of environments? And for a specific environment?**
- **What is the probability of a given selection candidate having better performance than a cultivar check in the target population of environments? And in specific environments?**
- **How probable is it that a given selection candidate performs similarly across environments?**
- **What are the chances that a given selection candidate is more stable than a cultivar check in the target population of environments?**
- **What is the probability that a given selection candidate having a superior and invariable performance across environments?**

More details about the usage of prob_sup, as well as the other function of the ProbBreed package can be found at https://saulo-chaves.github.io/ProbBreed_site/.

Value

The function returns an object of class `probsup`, which contains two lists, one with the across-environments probabilities, and another with the within-environments probabilities. If an entry-mean model was used in `ProbBreed::bayes_met`, only the across list will be available.

The across list has the following elements:

- `g_hpd`: Highest posterior density (HPD) of the posterior genotypic main effects.
- `perfo`: the probabilities of superior performance.
- `pair_perfo`: the pairwise probabilities of superior performance.
- `stabi`: a list with the probabilities of superior stability. It contains the data frames `gl`, `gm` (when `reg` is not `NULL`) and `gt` (when `year` is not `NULL`). Unavailable if an entry-mean model was used in `bayes_met`.
- `pair_stabi`: a list with the pairwise probabilities of superior stability. It contains the data frames `gl`, `gm` (when `reg` is not `NULL`) and `gt` (when `year` is not `NULL`). Unavailable if an entry-mean model was used in `bayes_met`.
- `joint_prob`: the joint probabilities of superior performance and stability. Unavailable if an entry-mean model was used in `bayes_met`.

The within list has the following elements:

- `perfo`: a list of data frames containing the probabilities of superior performance within locations (`gl`), regions (`gm`) and years (`gt`).
- `pair_perfo`: lists with the pairwise probabilities of superior performance within locations (`gl`), regions (`gm`) and years (`gt`).

References

- Dias, K. O. G, Santos J. P. R., Krause, M. D., Piepho H. -P., Guimarães, L. J. M., Pastina, M. M., and Garcia, A. A. F. (2022). Leveraging probability concepts for cultivar recommendation in multi-environment trials. *Theoretical and Applied Genetics*, 133(2):443-455. doi:[10.1007/s00122-02204041y](https://doi.org/10.1007/s00122-02204041y)
- Shukla, G. K. (1972) Some statistical aspects of partitioning genotype environmental componentes of variability. *Heredity*, 29:237-245. doi:[10.1038/hdy.1972.87](https://doi.org/10.1038/hdy.1972.87)

See Also

[plot.probsup](#)

Examples

```
mod = bayes_met(data = maize,
                gen = "Hybrid",
                loc = "Location",
                repl = c("Rep", "Block"),
                trait = "GY",
                reg = "Region",
                year = NULL,
                res.het = TRUE,
```

```

iter = 2000, cores = 2, chain = 4)

outs = extr_outs(model = mod,
  probs = c(0.05, 0.95),
  verbose = TRUE)

results = prob_sup(extr = outs,
  int = .2,
  increase = TRUE,
  save.df = FALSE,
  verbose = FALSE)

```

soy

Soybean real data set

Description

This dataset belongs to the USDA Northern Region Uniform Soybean Tests, and it is a subset of the data used by Krause et al. (2023). It contains the empirical best linear unbiased estimates of genotypic means of the seed yield from 39 experimental genotypes evaluated in 14 locations. The original data, available at the package SoyURT, has 4,257 experimental genotypes evaluated at 63 locations and 31 years resulting in 591 location-year combinations (environments) with 39,006 yield values.

Usage

soy

Format

soy:

A data frame with 823 rows and 3 columns:

Loc 14 locations**Gen** 39 experimental genotypes**Y** 435 EBLUEs (phenotypes)

Source

Krause MD, Dias KOG, Singh AK, Beavis WD. 2023. Using soybean historical field trial data to study genotype by environment variation and identify mega-environments with the integration of genetic and non-genetic factors. bioRxiv : the preprint server for biology. doi: <https://doi.org/10.1101/2022.04.11.487885>

Index

* datasets

maize, [7](#)

soy, [16](#)

bayes_met, [2](#), [6](#), [13](#)

bayes_met(), [6](#)

extr_outs, [6](#), [9](#), [11](#), [12](#)

ggplot2::geom_histogram, [8](#)

ggplot2::ggplot, [7](#)

maize, [7](#)

plot.extr, [7](#), [8](#)

plot.probsup, [9](#), [15](#)

print.extr, [11](#)

print.probsup, [12](#)

prob_sup, [10](#), [12](#), [12](#)

rstan::check_hmc_diagnostics, [7](#)

rstan::sampling, [6](#)

rstan::stan, [6](#)

rstan::stan_diag, [7](#)

rstan::stanfit, [6](#)

soy, [16](#)

stan, [4](#)