Package 'modEvA'

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Title Model Evaluation and Analysis

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Author Barbosa A.M., Brown J.A., Jimenez-Valverde A., Real R.

Maintainer A. Marcia Barbosa <barbosa@uevora.pt>

Description The modEvA package analyses species distribution models and evaluates their performance. It includes functions for performing variation partitioning, calculating several measures of model discrimination and calibration, optimizing prediction thresholds based on a number of criteria, performing multivariate environmental similarity surface (MESS) analysis, and displaying various analytical plots.

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LazyData yes

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`modEvA-package` *Model Evaluation and Analysis*

Description

The modEvA package can analyse species distribution models and evaluate their performance. It includes functions for performing variation partitioning, calculating several measures of model discrimination and calibration, optimizing prediction thresholds based on a number of criteria, performing multivariate environmental similarity surface (MESS) analysis, and displaying various analytical plots.

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Author(s)

Barbosa A.M., Brown J.A., Jimenez-Valverde A., Real R.

A. Marcia Barbosa <barbosa@uevora.pt>

References

Barbosa A.M., Real R., Munoz A.R. & Brown J.A. (2013) New measures for assessing model equilibrium and prediction mismatch in species distribution models. Diversity and Distributions

19: 1333-1338 (DOI: 10.1111/ddi.12100)

See Also

PresenceAbsence, **ROCR**, **verification**, **dismo**, **fuzzySim**

Examples

```
# load sample models:
data(rotif.mods)

# choose a particular model to play with:
mod <- rotif.mods$models[[1]]

# plot the 1st model:
plotGLM(model = mod)

# calculate the area under the ROC curve for the 1st model:
AUC(model = mod)

# calculate some more threshold-based measures for this model:
threshMeasures(model = mod, thresh = "preval")

# calculate optimal thresholds based on several criteria:
optiThresh(model = mod)

# calculate the optimal threshold balancing two evaluation measures:
optiPair(model = mod, measures = c("Omission", "Commission"))

# calculate the explained deviance, Hosmer-Lemeshow goodness-of-fit,
# Miller's calibration stats, and (pseudo) R-squared values for the 1st model:

Dsquared(model = mod)

HLfit(model = mod, bin.method = "quantiles")

MillerCalib(model = mod)

RsqGLM(model = mod)
```

---

arrangePlots *Arrange plots*

Description

Get an appropriate row/column combination (for `par(mfrow)`) for arranging a given number of plots within a plotting window.

Usage

```
arrangePlots(n.plots, landscape = FALSE)
```

Arguments

n.plots	number of plots to be placed in the graphics device.
landscape	logical, whether the plotting window should be landscape/horizontal (number of columns larger than the number of rows) or not. The value does not make a difference if the number of plots makes for a square plotting window.

Details

This function is used internally by optiThresh, but can also be useful outside it.

Value

An integer vector of the form c(nr, nc) indicating, respectively, the number of rows and of columns of plots to set in the graphics device.

Author(s)

A. Marcia Barbosa

See Also

plot, layout

Examples

```
arrangePlots(10)

arrangePlots(10, landscape = TRUE)


# a more practical example:

data(iris)

names(iris)

# say you want to plot all columns in a nicely arranged plotting window:

par(mfrow = arrangePlots(ncol(iris)))

for (i in 1:ncol(iris)) {
  plot(1:nrow(iris), iris[, i])
}
```

AUC *Area Under the ROC Curve*

Description

This function calculates the Area Under the Curve of the receiver operating characteristic (ROC) plot, for either a model object of class "glm", or two matching vectors of observed (binary, 1 for occurrence vs. 0 for non-occurrence) and predicted (continuous, e.g. occurrence probability) values, respectively. The AUC is a measure of the overall discrimination power of the predictions, or the probability that an occurrence site has a higher predicted value than a non-ocurrence site.

Usage

```
AUC(model = NULL, obs = NULL, pred = NULL, simplif = FALSE, interval = 0.01,
FPR.limits = c(0, 1), plot = TRUE, plot.values = TRUE, plot.preds = FALSE,
grid = FALSE, xlab = c("False positive rate", "(1-specificity)"),
ylab = c("True positive rate", "(sensitivity)"), main = "ROC curve", ...)
```

Arguments

model	a model object of class "glm".
obs	a vector of observed presences (1) and absences (0) or another binary response variable. Not necessary (and ignored) if model is provided.
pred	a vector with the corresponding predicted values of presence probability, habitat suitability, environmental favourability or alike. Must be of the same length and in the same order as obs. Not necessary (and ignored) if model is provided.
simplif	logical, whether to use a faster version that outputs only the AUC value (may be useful for calculating AUC for large numbers of species in a loop, for example). Note that the ROC plot is not drawn when simplif = TRUE.
FPR.limits	(NOT YET IMPLEMENTED) numerical vector of length 2 indicating the limits of false positive rate between which to calculate a partial AUC. The default is c(0, 1), for considering the whole AUC.
interval	interval of threshold values at which to calculate the true and false positive and negative rates. Defaults to 0.01. Ignored if simplif = TRUE. Note that this does not affect the obtained AUC value (although it can affect the size of the plotted ROC curve, especially when prevalence is low), as the AUC is calculated with the Mann-Whitney U statistic and is therefore threshold-independent.
plot	logical, whether or not to plot the ROC curve. Defaults to TRUE.
plot.values	logical, whether or not to show in the plot the values associated to the curve (e.g., the AUC). Defaults to TRUE.
plot.preds	logical, whether or not to plot the proportion of analysed model predictions (through proportionally sized circles) at each threshold. Experimental. Defaults to FALSE.
grid	logical, whether or not to add a grid to the plot, marking the analysed thresholds. Defaults to FALSE.

xlab	label for the x axis.
ylab	label for the y axis.
main	title for the plot.
...	further arguments to be passed to the plot function.

Details

Like the model evaluation measures calculated by the threshMeasures function, the area under the ROC curve (AUC) assesses the discrimination performance of a model; but unlike them, it does not require the choice of a particular threshold above which to consider that a model predicts species presence, but rather averages discrimination performance over all possible thresholds. Mind that the AUC has been widely criticized (e.g. Lobo et al. 2008, Jimenez-Valverde et al. 2013), yet it is still among the most widely used metrics in model evaluation. It is highly correlated with species prevalence, so this value is also provided by the AUC function (if simplif = FALSE, the default) for reference. Although there are functions to calculate the AUC in other R packages (e.g. **ROCR**, **PresenceAbsence**, **verification**, **Epi**), the AUC function is more compatible with the remaining functions in **modEvA** and can be applied not only to a set of observed versus predicted values, but also directly to a model object of class "glm".

Value

If simplif = TRUE, the function returns only the AUC value (a numeric value between 0 and 1). Otherwise (the default), it plots the curve and returns a list with the following components:

thresholds	a data frame of the true and false positives, the sensitivity and specificity of the predictions, and the number of predicted values at each analysed threshold.
N	the total number of obervations.
prevalence	the proportion of occurrences in the data (which correlates with the AUC).
AUC	the value of the AUC).
AUCratio	the ratio of the obtained AUC value to the null expectation (0.5).

Author(s)

A. Marcia Barbosa

References

Lobo, J.M., Jimenez-Valverde, A. & Real, R. (2008). AUC: a misleading measure of the performance of predictive distribution models. Global Ecology and Biogeography 17: 145-151

Jimenez-Valverde, A., Acevedo, P., Barbosa, A.M., Lobo, J.M. & Real, R. (2013). Discrimination capacity in species distribution models depends on the representativeness of the environmental domain. Global Ecology and Biogeography 22: 508-516

See Also

threshMeasures

Examples

```
# load sample models:
data(rotif.mods)

# choose a particular model to play with:
mod <- rotif.mods$models[[1]]


AUC(model = mod, simplif = TRUE)

AUC(model = mod)

AUC(model = mod, grid = TRUE, plot.preds = TRUE)


# you can also use AUC with vectors of observed and predicted values
# instead of with a model object:

presabs <- mod$y
prediction <- mod$fitted.values

AUC(obs = presabs, pred = prediction)
```

`Dsquared` *Proportion of deviance explained by a GLM*

Description

This function calculates the (adjusted) amount of deviance accounted for by a generalized linear model.

Usage

```
Dsquared(model = NULL, obs = NULL, pred = NULL, family = NULL, adjust = FALSE, npar = NULL)
```

Arguments

`model`	a model object of class "glm".
`obs`	a numeric vector of the observed data. Not necessary (and ignored) if `model` is provided.
`pred`	a numeric vector of the values predicted by a GLM of the observed data. Not necessary (and ignored) if `model` is provided. Must be of the same length and in the same order as `obs`.
`family`	a character vector (i.e. in quotes) of length 1 specifying the family of the GLM. Not necessary (and ignored) if `model` is provided; otherwise (i.e. if 'obs' and 'pred' are provided rather than a model object), only families 'binomial' (logit link) and 'poisson' (log link) are currently implemented.

adjust	logical, whether or not to adjust the D-squared value for the number of observations and parameters in the model (see Details). The default is FALSE; TRUE requires either providing the model object, or specifying the number of parameters in the model that produced the pred values.
npar	an integer vector indicating the number of parameters in the model. Not necessary (and ignored) if model is provided or if adjust = FALSE.

Details

Linear models come with an R-squared value that measures the proportion of variation that the model accounts for. The R-squared is provided with summary(model) in R. For generalized linear models (GLMs), the equivalent is the amount of deviance accounted for (D-squared; Guisan & Zimmermann 2000), but this value is not normally provided with the model summary. The Dsquared function calculates it. There is also an option to calculate the adjusted D-squared, which takes into account the number of observations and the number of predictors, thus allowing direct comparison among different models (Weisberg 1980, Guisan & Zimmermann 2000).

Value

This functin returns a numeric value indicating the (adjusted) proportion of deviance accounted for by the model.

Author(s)

A. Marcia Barbosa

References

Guisan, A. & Zimmermann, N.E. (2000) Predictive habitat distribution models in ecology. Ecological Modelling 135: 147-186

Weisberg, S. (1980) Applied Linear Regression. Wiley, New York

See Also

glm, plotGLM

Examples

```
# load sample models:
data(rotif.mods)

# choose a particular model to play with:
mod <- rotif.mods$models[[1]]

Dsquared(model = mod)

Dsquared(model = mod, adjust = TRUE)


# you can also use \code{Dsquared} with vectors of observed and predicted values
```

```
# instead of with a model object:

presabs <- mod$y
prediction <- mod$fitted.values
parameters <- attributes(logLik(mod))$df

Dsquared(obs = presabs, pred = prediction, family = "binomial")

Dsquared(obs = presabs, pred = prediction, family = "binomial", adjust = TRUE, npar = parameters)
```

`evaluate` *Evaluate a GLM based on the elements of a confusion matrix.*

Description

This functions evaluates the discrimination performance of a model based on the values of a confusion matrix obtained at a particular threshold.

Usage

```
evaluate(a, b, c, d, N = NULL, measure = "CCR")
```

Arguments

`a`	number of correctly predicted presences
`b`	number of absences incorrectly predicted as presences
`c`	number of presences incorrectly predicted as absences
`d`	number of correctly predicted absences
`N`	total number of cases. If NULL (the dafault) it is calculated automatically by adding up a, b, c and d.)
`measure`	a character vector of length 1 indicating the the evaluation measure to use. Type `modEvAmethods("threshMeasures")` for available options.

Details

A number of measures can be used to evaluate continuous model predictions against observed binary occurrence data (Fielding & Bell 1997; Liu et al. 2011; Barbosa et al. 2013). The `evaluate` function can calculate a few threshold-based discrimination measures from the values of a confusion matrix obtained at a particular threshold. The `evaluate` function is used internally by `threshMeasures`. It can also be accessed directly by the user, but it is usually more practical to use `threshMeasures`, which calculates the confusion matrix automatically.

Value

The value of the specified evaluation measure.

Author(s)

A. Marcia Barbosa

References

Barbosa A.M., Real R., Munoz A.R. & Brown J.A. (2013) New measures for assessing model equilibrium and prediction mismatch in species distribution models. Diversity and Distributions, 19: 1333-1338

Fielding A.H. & Bell J.F. (1997) A review of methods for the assessment of prediction errors in conservation presence/absence models. Environmental Conservation 24: 38-49

Liu C., White M., & Newell G. (2011) Measuring and comparing the accuracy of species distribution models with presence-absence data. Ecography, 34, 232-243.

See Also

threshMeasures

Examples

```
evaluate(23, 44, 21, 34)

evaluate(23, 44, 21, 34, measure = "TSS")
```

---

evenness *Evenness in a binary vector.*

Description

For building and evaluating species distribution models, the porportion of presences (prevalence) of a species and the balance between the number of presences and absences may be issues to take into account (e.g. Jimenez-Valverde & Lobo 2006, Barbosa et al. 2013). The evenness function calculates the presence-absence balance in a binary (e.g., presence/absence) vector.

Usage

```
evenness(obs)
```

Arguments

obs	a vector of binary observations (e.g. 1 or 0, male or female, disease or no disease, etc.)

Value

A number ranging between 0 when all values are the same, and 1 when there are the same number of cases with each value in obs.

Author(s)

A. Marcia Barbosa

References

Barbosa A.M., Real R., Munoz A.R. & Brown J.A. (2013) New measures for assessing model equilibrium and prediction mismatch in species distribution models. Diversity and Distributions, 19: 1333-1338

Jimenez-Valverde A. & Lobo J.M. (2006) The ghost of unbalanced species distribution data in geographical model predictions. Diversity and Distributions, 12: 521-524.

See Also

prevalence

Examples

```
(x <- rep(c(0, 1), each = 5))
(y <- c(rep(0, 3), rep(1, 7)))
(z <- c(rep(0, 7), rep(1, 3)))

prevalence(x)
evenness(x)

prevalence(y)
evenness(y)

prevalence(z)
evenness(z)
```

---

getBins *Get bins of data.*

Description

Get continuous predicted values into bins according to specific criteria.

Usage

```
getBins(model = NULL, obs = NULL, pred = NULL, id = NULL, bin.method = "quantiles",
n.bins = 10, fixed.bin.size = FALSE, min.bin.size = 15, min.prob.interval = 0.1,
simplif = FALSE)
```

Arguments

model	a model object of class "glm".
obs	a vector of 1-0 values of a modelled binary variable. Not necessary (and ignored) if model is provided.
pred	a vector of the corresponding predicted values. Not necessary (and ignored) if model is provided.
id	optional vector of row identifiers; must be of the same length and in the same order of obs and pred (or of the cases used to build model)
bin.method	the method with which to divide the values into bins. Type modEvAmethods("getBins") for available options.
n.bins	the number of bins in which to divide the data.
fixed.bin.size	logical, whether all bins should have the same size.
min.bin.size	integer value defining the minimum number of observations to include in each bin. The default minimum is 15, following Jovani & Tella (2006).
min.prob.interval	minimum range of probability values in each bin. Defaults to 0.1.
simplif	logical, whether to calculate a simplified faster version (usd internally in other functions). The default is FALSE.

Value

The output of getBins is a list with the following components:

prob.bin	the first and last value of each bin
bins.table	a data frame with the numbers of presences, absences, prevalence, mean probability, etc. in each bin.
N	the total number of observations in the analysis.
n.bins	the total number of bins obtained.

Author(s)

A. Marcia Barbosa

References

Jovani R. & Tella J.L. (2006) Parasite prevalence and sample size: misconceptions and solutions. Trends in Parasitology 22: 214-218.

See Also

HLfit

Examples

```
# load sample models:
data(rotif.mods)

# choose a particular model to play with:
mod <- rotif.mods$models[[1]]

getBins(model = mod)
```

`getModEqn` *Get model equation*

Description

This function retrieves the equation of a model, to print or apply elsewhere.

Usage

```
getModEqn(model, type = "Y", digits = NULL, prefix = NULL, suffix = NULL)
```

Arguments

`model`	a model object of class 'lm' or glm'.
`type`	the type of equation to get; can be either "Y" (the default, for the linear model equation), "P" (for probabiity) or "F" (for favourability).
`digits`	the number of digits to which to round the coefficient estimates in the equation.
`prefix`	the prefix to add to each variable name in the equation.
`suffix`	the suffix to add to each variable name in the equation.

Details

The summary of a model in R gives you a table of the coefficient estimates and other parameters. Sometimes it may be useful to have a string of text with the model's equation, so that you can present it in an article (e.g. Real et al. 2005) or apply it in a (raster map) calculation, either in R (although here you can usually use the 'predict' function for this) or in a GIS software (e.g. Barbosa et al. 2010). The `getModEqn` function gets this equation for linear or generalized linear models.

By default it prints the `"Y"` linear equation, but for generalized linear models you can also set `type = "P"` (for the equation of probability) or `type = "F"` (for favourability, which corrects the intercept to eliminate the effect of prevalence - see Real et al. 2006).

If the variables to which you want to apply the model have a prefix or suffix (e.g. prefix = "raster.stack$" for the R raster package, or prefix = "mydata$" for a data frame, or suffix = "@1" in Quantum GIS, or suffix = "@mapset" in GRASS), you can get these in the equation too, using the `prefix` and/or the `suffix` argument.

Value

A charachter string of model the equation.

Author(s)

A. Marcia Barbosa

References

Barbosa A.M., Real R. & Vargas J.M. (2010) Use of coarse-resolution models of species' distributions to guide local conservation inferences. Conservation Biology 24: 1378-87

Real R., Barbosa A.M., Martinez-Solano I. & Garcia-Paris, M. (2005) Distinguishing the distributions of two cryptic frogs (Anura: Discoglossidae) using molecular data and environmental modeling. Canadian Journal of Zoology 83: 536-545

Real R., Barbosa A.M. & Vargas J.M. (2006) Obtaining environmental favourability functions from logistic regression. Environmental and Ecological Statistics 13: 237-245

Examples

```
# load sample models:
data(rotif.mods)

# choose a particular model to play with:
mod <- rotif.mods$models[[1]]

getModEqn(mod)

getModEqn(mod, type = "P", digits = 3, suffix = "@mapset")

getModEqn(mod, type = "F", digits = 2)
```

HLfit *Hosmer-Lemeshow goodness of fit*

Description

Calculate a model's calibration performance (reliability) with the Hosmer & Lemeshow goodness-of-fit statistic.

Usage

```
HLfit(model = NULL, obs = NULL, pred = NULL, bin.method, n.bins = 10,
fixed.bin.size = FALSE, min.bin.size = 15, min.prob.interval = 0.1, simplif = FALSE,
alpha = 0.05, plot = TRUE, plot.values = TRUE, plot.bin.size = TRUE,
xlab = "Predicted probability", ylab = "Observed prevalence", ...)
```

Arguments

model	a model object of class "glm".
obs	a vector of observed presences (1) and absences (0) or another binary response variable. Not necessary (and ignored) if model is provided.
pred	a vector with the corresponding predicted probabilities as given e.g. by logistic regression. Not necessary (and ignored) if model is provided.
bin.method	the method for grouping the records into bins within which to compare predicted probability to observed prevalence; type modEvAmethods("getBins") for available options. See Details for more info.
n.bins	the number of bins to use if bin.method = n.bins.
fixed.bin.size	logical, whether to force bins to have the same size whenever possible.
min.bin.size	the minimum number of records in each bin (minimum for significant comparisons is at least 15 according to Jovani & Tella 2006).
min.prob.interval	the minimum interval (range) of probability values within each bin.
simplif	logical, wheter to perform a faster version returning only the basic statistics.
alpha	alpha value for confidence intervals if plot = TRUE.
plot	logical, whether to produce a plot of the results.
plot.values	logical, whether to report measure values in the plot.
plot.bin.size	logical, whether to report bin sizes in the plot.
xlab	label for the x axis.
ylab	label for the y axis.
...	further arguments to pass to the plot function.

Details

Most of the commonly used measures for evaluating model performance focus on discrimination capacity, i.e., how well the model is capable of distinguishing presences from absences (after the model's continuous predictions of presence probability or alike are converted to binary predictions of presence or absence). However, there is another important facet of model evaluation: calibration or reliability, i.e., the relationship between predicted probability and observed prevalence (Pearce & Ferrier 2000; Jimenez-Valverde et al. 2013). The HLfit function measures model reliability with the Hosmer & Lemeshow goodness-of-fit statistic (Hosmer & Lemeshow 1980).

Note that this statistic has some limitations and caveats (see e.g. http://www.statisticalhorizons.com/hosmer-lemeshow), mainly due to the need to group the values into bins within which to compare probability and prevalence, and the influence of the binning method on the result. The HLfit function can use several binning methods, which are implemented in the getBins function and can be accessed by typing modEvAmethods("getBins"). You should therefore evaluate your model using different binning methods, to see if the results change significantly.

Value

HLfit returns a list with the following components:

bins.table	a data frame of the obtained bins and the values resulting from the hosmer-Lemeshow goodness-of-fit analysis.
chi.sq	the value of the Chi-squared test.
DF	the number of degrees of freedom.
p.value	the p-value of the Hosmer-Lemeshow test. Note that this is one of those tests for which higher p-values are better.
RMSE	the root mean squared error.

Note

The 4 lines of code from "observed" to "p.value" were adapted from the 'hosmerlem' function available at http://www.stat.sc.edu/~hitchcock/diseaseoutbreakRexample704.txt. The plotting code was loosely based on the calibration.plot function in package **PresenceAbsence**. HLfit still needs some code simplification, and may fail for some datasets and binning methods. Fixes are being applied. Feedback is welcome.

Author(s)

A. Marcia Barbosa

References

Hosmer D.W. & Lemeshow S. (1980) A goodness-of-fit test for the multiple logistic regression model. Communications in Statistics, A10: 1043-1069

Jimenez-Valverde A., Acevedo P., Barbosa A.M., Lobo J.M. & Real R. (2013) Discrimination capacity in species distribution models depends on the representativeness of the environmental domain. Global Ecology and Biogeography, 22: 508-516

Jovani R. & Tella J.L. (2006) Parasite prevalence and sample size: misconceptions and solutions. Trends in Parasitology 22: 214-218

Pearce J. & Ferrier S. (2000) Evaluating the Predictive Performance of Habitat Models Developed using Logistic Regression. Ecological Modeling, 133: 225-245

See Also

getBins, threshMeasures, AUC

Examples

```
# load sample models:
data(rotif.mods)

# choose a particular model to play with:
mod <- rotif.mods$models[[1]]

HLfit(model = mod, bin.method = "n.bins", min.prob.interval = 0.1)
```

```
HLfit(obs = mod$y, pred = mod$fitted.values, bin.method = "quantiles", n.bins = 10)
```

`MESS` *Multivariate Environmental Similarity Surfaces based on a data frame*

Description

This function performs the MESS analysis of Elith et al. (2010) to determine the extent of the environmental differences between model training and model projection (extrapolation) data. It is applicable to variables in a matrix or data frame.

Usage

```
MESS(V, P)
```

Arguments

`V`	a matrix or data frame containing the variables (one in each column) in the reference (training) dataset.
`P`	a matrix or data frame containing the same variables in the area to which the model(s) will be projected. Variables (columns) must be in the same order as in `V`, and `colnames(P)` must exist.

Details

When model predictions are projected into regions, times or spatial resolutions not analysed in the training data, it may be important to measure the similarity between the new environments and those in the training sample (Elith et al. 2010), as models are not so reliable when predicting outside their domain (Barbosa et al. 2009). The Multivariate Environmental Similarity Surfaces (MESS) analysis measures the similarity in the analysed variables between any given locality in the projection dataset and the localities in the reference (training) dataset (Elith et al. 2010).

MESS analysis is implemented in the MAXENT software (Phillips et al. 2006) and in the **dismo** R package, but there it requires input variables in raster format. This implies not only the use of complex spatial data structures, but also that the units of analysis are rectangular pixels, whereas we often need to model distribution data recorded on irregular units (e.g. provinces, river basins), or on equal-area units (e.g. UTM cells, equal-area hexagons), whereas pixels vary in area between the equator and the poles. The MESS function computes this analysis for variables in a data frame, where localities (in rows) may be of any size or shape.

Value

The function returns a data frame with the same column names as `P`, plus a column named `TOTAL`, quantifying the similarity between each point in the projection dataset and those in the reference dataset. Negative values indicate localities that are environmentally dissimilar from the reference region. The last column, `MoD`, indicates which of the column names of P corresponds to the most dissimilar variable, i.e., the limiting factor or the variable that drives the MESS in that locality (Elith et al. 2010).

Note

A new, apparently more complete method for analysing environmental dissimilarities has recently become available (see https://www.climond.org/ExDet.aspx). We are planning on implementing a dataframe version of that too.

Author(s)

Alberto Jimenez-Valverde, A. Marcia Barbosa

References

Barbosa A.M., Real R. & Vargas J.M. (2009) Transferability of environmental favourability models in geographic space: the case of the Iberian desman (Galemys pyrenaicus) in Portugal and Spain. Ecological Modelling 220: 747-754

Elith J., Kearney M. & Phillips S. (2010) The art of modelling range-shifting species. Methods in Ecology and Evolution 1: 330-342

Phillips S.J., Anderson R.P. & Schapire R.E. (2006) Maximum entropy modeling of species geographic distributions. Ecological Modelling 190: 231-259

See Also

`mess` in package **dismo**; `OA`

Examples

```
## Not run:
# load package fuzzySim (currently available on R-Forge) and its sample data:
require(fuzzySim)
data(rotif.env)


# add a column specifying the hemisphere:

unique(rotif.env$CONTINENT)

rotif.env$HEMISPHERE <- "Eastern"

rotif.env$HEMISPHERE[rotif.env$CONTINENT %in%
c("NORTHERN_AMERICA", "SOUTHERN_AMERICA")] <- "Western"

head(rotif.env)


# perform a MESS analysis
# suppose you'll extrapolate models from the Western hemisphere (Americas)
# to the Eastern hemisphere (rest of the world):

names(rotif.env)  # variables are in columns 5:17

mess <- MESS(V = subset(rotif.env, HEMISPHERE == "Western", select = 5:17),
```

```
P = subset(rotif.env, HEMISPHERE == "Eastern", select = 5:17))

head(mess)
range(mess[ , "TOTAL"])

## End(Not run)
```

`MillerCalib` *Miller's calibration satistics for logistic regression models*

Description

This function calculates Miller's (1991) calibration statistics for a generalized linear model with binomial distribution and logistic link, namely the intercept and slope of the regression of the response variable on the logit of predicted probabilities. Optionally and by default, it also plots the corresponding regression line (black) over the reference diagonal (grey).

Usage

```
MillerCalib(model = NULL, obs = NULL, pred = NULL, plot = TRUE,
plot.values = TRUE, digits = 4, xlab = "", ylab = "",
main = "Miller calibration", ...)
```

Arguments

`model`	a model object of class "glm" and family "binomial".
`obs`	a vector of observed presences (1) and absences (0) or another binary response variable. Not necessary (and ignored) if `model` is provided.
`pred`	a vector with the corresponding predicted values of presence probability. Must be of the same length and in the same order as `obs`. Not necessary (and ignored) if `model` is provided.
`plot`	logical, whether to plot the regression line over the reference diagonal. Defaults to TRUE.
`plot.values`	logical value indicating whether to report the statistics in the plot. Defaults to TRUE.
`digits`	integer number indicating the number of digits to which the values in the plot should be rounded. Dafaults to 4. Ignored if `plot` or `plot.values` are set to `FALSE`.
`xlab`	label for the x axis.
`ylab`	label for the y axis.
`main`	title for the plot.
`...`	additional arguments to pass to `plot`.

Details

Calibration or reliability measures how a model's predicted probabilities relate to observed species prevalence or proportion of presences in the modelled data (Pearce & Ferrier 2000; Wintle et al. 2005; Franklin 2010). If predictions are perfectly calibrated, the slope will equal 1 and the intercept will equal 0, so the model's calibation line will perfectly overlap with the reference diagonal. Note that Miller's statistics assess the model globally: a model is well calibrated if the average of all predicted probabilities equals the proportion of presences in the modelled data. Good calibration is always attained on the same data used for building the model (Miller 1991).

Value

This function returns a list of three integer values:

`intercept`	the calibration intercept.
`slope`	the calibration slope.
`slope.pvalue`	the significance of the difference between our slope and the ideal slope of 1, calculated according to Paternoster et al. (1998).

If `plot = TRUE`, a plot will be produced with the model calibration line (black) over the reference diagonal (dashed grey), optionally (if `plot.values = TRUE`) with the values printed on it.

Author(s)

A. Marcia Barbosa

References

Franklin, J. (2010) Mapping Species Distributions: Spatial Inference and Prediction. Cambridge University Press, Cambridge.

Miller M.E., Hui S.L. & Tierney W.M. (1991) Validation techniques for logistic regression models. Statistics in Medicine, 10: 1213-1226

Paternoster R., Brame R., Mazerolle P. & Piquero A.R. (1998) Using the correct statistical test for the equality of regression coefficients. Criminology, 36(4): 859-866

Pearce J. & Ferrier S. (2000) Evaluating the predictive performance of habitat models developed using logistic regression. Ecological Modelling, 133: 225-245

Wintle B.A., Elith J. & Potts J.M. (2005) Fauna habitat modelling and mapping: A review and case study in the Lower Hunter Central Coast region of NSW. Austral Ecology, 30: 719-738

See Also

`HLfit`, `Dsquared`, `RsqGLM`

Examples

```
# load sample models:
data(rotif.mods)

# choose a particular model to play with:
```

```
mod <- rotif.mods$models[[1]]

MillerCalib(model = mod)


# you can also use MillerCalib with vectors of observed and predicted values
# instead of a model object:

MillerCalib(obs = mod$y, pred = mod$fitted.values)
```

---

modEvAmethods *Methods implemented in modEvA functions*

Description

This function allows retrieving the methods available for some of the functions in modEvA, such as threshMeasures, optiThresh, multModEv and getBins.

Usage

```
modEvAmethods(fun)
```

Arguments

fun	a character vector of length 1 specifying the name (in quotes) of the function for which to obtain the available methods.

Value

a character vector of the available methods for the specified function.

Author(s)

A. Marcia Barbosa

See Also

threshMeasures, optiThresh, getBins, multModEv

Examples

```
modEvAmethods("threshMeasures")

modEvAmethods("multModEv")

modEvAmethods("optiThresh")

modEvAmethods("getBins")
```

`multModEv` *Multiple model evaluation*

Description

If you have a list of models created e.g. with the `multGLM` function of the **fuzzySim** package, or a data frame with presence-absence data and the corresponding predicted values for a set of species, you can use the `multModEv` function to get a set of evaluation measures for all models simultaneously. Note that all models must have the same sample size.

Usage

```
multModEv(models = NULL, obs.data = NULL, pred.data = NULL,
measures = modEvAmethods("multModEv"), standardize = FALSE, thresh = 0.5,
bin.method = "quantiles", quiet = TRUE)
```

Arguments

`models`	a `list` of model object(s) of class "glm", all applied to the same data set.
`obs.data`	a data frame with observed binary data. Not necessary (and ignored) if `models` is provided.
`pred.data`	a data frame with the corresponding predicted probability values, with both rows and columns in the same order as in `obs.data`. Not necessary (and ignored) if `models` is provided.
`measures`	character vector of the evaluation measures to calculate. The default is all implemented measures, which you can check by typing `modEvAmethods("multModEv")`.
`standardize`	logical, whether to standardize measures that vary between -1 and 1 to the 0-1 scale (see `standard01`).
`thresh`	the threshold value to use for calculating threshold-based measures (the ones in `modEvAmethods("threshMeasures")`). Can be "preval" (for species prevalence) or any number between 0 and 1. The default is 0.5.
`bin.method`	the method with which to divide the data into groups or bins (for calibration or reliability measures such as `HLfit`); type modEvAmethods("getBins") for available options).
`quiet`	logical, whether to be quiet or display messages.

Value

A data frame with the value of each evaluation measure for each model.

Author(s)

A. Marcia Barbosa

See Also

threshMeasures

Examples

```
data(rotif.mods)

eval <- multModEv(models = rotif.mods$models, thresh = "preval",
measures = c("AUC", "CCR", "Sensitivity", "TSS", "HL.p"))

head(eval)


# you can also calculate evaluation measures for a set of
# observed vs predicted data, rather than from model objects:

## Not run:
require(fuzzySim)  # currently available on R-Forge
data(rotif.env)

eval <- multModEv(obs.data = rotif.env[ , 18:20],
pred.data = rotif.mods$predictions[ , c("Abrigh_P", "Afissa_P", "Apriod_P")],
thresh = "preval")

head(eval)

## End(Not run)
```

OA *Overlap Analysis*

Description

This function analyses the range of values of the given environmental variables at the sites where a species has been recorded present.

Usage

```
OA(data, sp.cols, var.cols)
```

Arguments

data	a data frame with your species' occurrence data and the predictor variables.
sp.cols	index number of the column containing the occurrence data of the species to be modelled. Currently only one species can be analysed at a time.
var.cols	index numbers of the columns containing the predictor variables to be used.

Details

Overlap Analysis is one of the simplest forms of modelling species' distributions. It assesses the ranges of values of the given environmental variables at the sites where a species has been recorded present, and predicts where that species should be able to occur based on those presence data (e.g. Brito et al. 1999, Arntzen & Teixeira 2006).

OA can also be useful when extrapolating models outside their original scope (geographical area, time period or spatial resolution), as it can identify which localities are within the model's domain - i.e., within the analysed ranges of values of the variables, outside which the model may not be reliable (e.g. Barbosa et al. 2009). In this case, the response is not a species' presence, but rather the sites that have been included in the model. See also the MESS function for a comparison between modelled and extrapolation environments.

Input data for the OA function are a vector or column with ones and zeros (presences vs. absences of a species if we want to model its occurrence, or modelled vs. non-modelled sites if we want to know which non-modelled sites are within the modelled range), and a matrix or data frame with the corresponding values of the environmental variables to consider (one variable in each column, values in rows).

Value

A binary vector whith 1 where the values of all predictors lie within the ranges observed for the presence records, and 0 otherwise.

Author(s)

A. Marcia Barbosa

References

Arntzen J.W, Teixeira J. (2006) History and new developments in the mapping and modelling of the distribution of the golden-striped salamander, Chioglossa lusitanica. Zeitschrift fur Feldherpetologie, Supplement: 1-14.

Barbosa, A.M., Real, R. & Vargas, J.M. (2009) Transferability of environmental favourability models in geographic space: the case of the Iberian desman (Galemys pyrenaicus) in Portugal and Spain. Ecological Modelling 220: 747-754.

Brito J.C., Crespo E.G., Paulo O.S. (1999) Modelling wildlife distributions: Logistic Multiple Regression vs Overlap Analysis. Ecography 22: 251-260.

See Also

MESS

Examples

```
## Not run:
# load package fuzzySim (currently available on R-Forge) and its sample data:
require(fuzzySim)
data(rotif.env)
```

```
names(rotif.env)

OA(rotif.env, sp.cols = 18, var.cols = 5:17)

## End(Not run)
```

---

optiPair *Optimize the discrimination threshold for a pair of related model evaluation measures.*

Description

The optiPair function can optimize a model's discrimination threshold based on a pair of model evaluation measures that balance each other, such as sensitivity-specificity, omission-commission, or underprediction-overprediction (Fielding & Bell 1997; Liu et al. 2011; Barbosa et al. 2013). The function plots both measures in the given pair against all thresholds with a given interval, and calculates the optimal sum, difference and mean of the two measures.

Usage

```
optiPair(model = NULL, obs = NULL, pred = NULL,
measures = c("Sensitivity", "Specificity"), interval = 0.01, plot = TRUE,
plot.sum = FALSE, plot.diff = FALSE, ylim = NULL, ...)
```

Arguments

model	a model object of class "glm".
obs	a vector of observed presences (1) and absences (0) or another binary response variable. Not necessary (and ignored) if model is provided.
pred	a vector with the corresponding predicted values of presence probability, habitat suitability, environmental favourability or alike. Not necessary (and ignored) if model is provided.
measures	a character vector of length 2 indicating the pair of measures whose curves to plot and whose thresholds to optimize. The default is c("Sensitivity", "Specificity").
interval	the interval of thresholds at which to calculate the measures. The default is 0.01.
plot	logical indicating whether or not to plot the pair of measures.
plot.sum	logical, whether to plot the sum (+) of both measures in the pair. Defaults to FALSE.
plot.diff	logical, whether to plot the difference (-) between both measures in the pair. Defaults to FALSE.
ylim	a character vector of length 2 indicating the lower and upper limits for the y axis. The default is NULL for an automatic definition of ylim based on the values of the measures and their sum and/or difference if any of these are set to TRUE.
...	additional arguments to be passed to the plot function.

Value

The output is a list with the following components:

`measures.values`
: a data frame with the values of the chosen pair of measures, as well as their difference, sum and mean, at each threshold.

`MinDiff`
: numeric value, the minimum difference between both measures.

`ThreshDiff`
: numeric value, the threshold that minimizes the difference between both measures.

`MaxSum`
: numeric value, the maximum sum of both measures.

`ThreshSum`
: numeric value, the threshold that maximizes the sum of both measures.

`MaxMean`
: numeric value, the maximum mean of both measures.

`ThreshMean`
: numeric value, the threshold that maximizes the mean of both measures.

Author(s)

A. Marcia Barbosa

References

Barbosa, A.M., Real, R., Munoz, A.-R. & Brown, J.A. (2013) New measures for assessing model equilibrium and prediction mismatch in species distribution models. Diversity and Distributions 19: 1333-1338

Fielding A.H. & Bell J.F. (1997) A review of methods for the assessment of prediction errors in conservation presence/absence models. Environmental Conservation 24: 38-49

Liu C., White M., & Newell G. (2011) Measuring and comparing the accuracy of species distribution models with presence-absence data. Ecography, 34, 232-243.

See Also

optiThresh, threshMeasures

Examples

```
# load sample models:
data(rotif.mods)

# choose a particular model to play with:
mod <- rotif.mods$models[[1]]

optiPair(model = mod)

optiPair(model = mod, measures = c("UPR", "OPR"))


# you can also use optiPair with vectors of observed and predicted values
# instead of with a model object:
```

```
optiPair(obs = mod$y, pred = mod$fitted.values, measures = c("Omission",
"Commission"))
```

---

optiThresh *Optimize threshold for model evaluation.*

Description

The optiThresh function calculates optimal thresholds for a number of model evaluation measures (see threshMeasures). Optimization is given for each measure, and/or for all measures according to particular criteria (e.g. Jimenez-Valverde & Lobo 2007, Nenzen & Araujo 2011). Results are given numerically and in plots.

Usage

```
optiThresh(model = NULL, obs = NULL, pred = NULL, interval = 0.01,
measures = modEvAmethods("threshMeasures"), optimize = modEvAmethods("optiThresh"),
simplif = FALSE, plot = TRUE, sep.plots = FALSE, xlab = "Threshold", ...)
```

Arguments

model	a model object of class "glm".
obs	a vector of observed presences (1) and absences (0) or another binary response variable. Not necessary (and ignored) if model is provided.
pred	a vector with the corresponding predicted values of presence probability, habitat suitability, environmental favourability or alike. Not necessary (and ignored) if model is provided.
interval	numeric value between 0 and 1 indicating the interval between the thresholds at which to calculate the evaluation measures. Defaults to 0.01.
measures	character vector indicating the names of the model evaluation measures for which to calculate optimal thresholds. The default is using all measures available in modEvAmethods("threshMeasures").
optimize	character vector indicating the threshold optimization criteria to use; "each" calculates the optimal threshold for each model evaluation measure, while the remaining options optimize all measures according to the specified criterion. The default is using all criteria available in modEvAmethods("optiThresh").
simplif	logical, whether to calculate a faster simplified version. Used internally in other functions.
plot	logical, whether to plot the values of each evaluation measure at all thresholds.
sep.plots	logical. If TRUE, each plot is presented separately (you need to be recording R plot history to be able to browse through them all); if FALSE (the default), all plots are presented together in the same plotting window.
xlab	character vector indicating the label of the x axis.
...	additional arguments to pass to plot.

Value

This function returns a list with the following components:

`all.thresholds` a data frame with the values of all analysed measures at all analysed thresholds.

`optimals.each` if "each" is among the threshold criteria specified in `optimize`, optimals.each is output as a data frame with the value of each measure at its optimal threshold, as well as the type of optimal for that measure (which may be the maximum for measures of goodness such as "Sensitivity", or the minimum for measures of badness such as "Omission").

`optimals.criteria` a data frame with the values of measure at the threshold that maximizes each of the criteria specified in `optimize` (except for `"each"`, see above).

Note

Some measures cannot be calculated for thresholds at which there are zeros in the confusion matrix, hence the eventual 'NaN' or 'Inf' in results. Also, optimization may be deceiving for some measures; use `plot = TRUE` and inspect the plot(s).

Author(s)

A. Marcia Barbosa

References

Jimenez-Valverde A. & Lobo J.M. (2007) Threshold criteria for conversion of probability of species presence to either-or presence-absence. Acta Oecologica 31: 361-369.

Nenzen H.K. & Araujo M.B. (2011) Choice of threshold alters projections of species range shifts under climate change. Ecological Modelling 222: 3346-3354.

See Also

`threshMeasures`, `optiPair`

Examples

```
# load sample models:
data(rotif.mods)

# choose a particular model to play with:
mod <- rotif.mods$models[[1]]

optiThresh(model = mod)


# change some of the parameters:

optiThresh(model = mod, pch = 20, measures = c("CCR", "Sensitivity", "Specificity",
"UPR", "OPR", "kappa", "TSS"), ylim = c(0, 1))
```

```
# you can also use optiThresh with vectors of observed and predicted values
# instead of with a model object:

optiThresh(obs = mod$y, pred = mod$fitted.values, pch = ".")
```

---

plotGLM *Plot a generalized linear model*

Description

This function plots the observed (presence/absence) data and the predicted (probability) values of a Generalized Linear Model against the y regression equation (logit) values. Only logistic regression (binomial response, logit link) is implemented. Optionally (if `plot.values = TRUE`) it can display in the plot the proportion of deviance explained (Weisberg 1980, Guisan & Zimmermann 2000).

Usage

```
plotGLM(model = NULL, obs = NULL, pred = NULL, link = "logit", plot.values = FALSE,
xlab = "Logit (Y)", ylab = "Predicted probability", main = "Model plot", ...)
```

Arguments

`model`	a model object of class "glm".
`obs`	a vector of presence/absence or other binary (1-0) observed data. Not necessary (and ignored) if `model` is provided.
`pred`	a vector of the values predicted by a GLM of the binary observed data. Not necessary (and ignored) if `model` is provided.
`link`	the link function of the GLM; only 'logit' (the default) is implemented.
`plot.values`	logical, whether to report values associated with the model in the plot (see Details). Defaults to `FALSE`.
`xlab`	character string specifying the label for the x axis.
`ylab`	character string specifying the label for the y axis.
`main`	character string specifying the title for the plot.
`...`	additional arguments to pass to `plot`.

Details

If `plot.values = TRUE`, the plot will also display values such as deviance (and adjusted deviance if `model` is provided). Deviance is calculated with the `Dsquared` function. Additional measures will be implemented in the future.

Value

This function outputs a plot of the provided model.

Author(s)

A. Marcia Barbosa

References

Guisan A. & Zimmermann N.E. (2000) Predictive habitat distribution models in ecology. Ecological Modelling 135: 147-186

Weisberg S. (1980) Applied Linear Regression. Wiley, New York

See Also

glm, Dsquared

Examples

```
# load sample models:
data(rotif.mods)

# choose a particular model to play with:
mod <- rotif.mods$models[[1]]

plotGLM(model = mod)

plotGLM(model = mod, plot.values = TRUE)


# you can also use \code{plotGLM} with vectors of observed and predicted values
# instead of with a model object:

plotGLM(obs = mod$y, pred = mod$fitted.values)
```

---

prevalence *Prevalence*

Description

For building and evaluating species distribution models, the porportion of presences of the species may be issues to take into account (e.g. Jimenez-Valverde & Lobo 2006, Barbosa et al. 2013). The prevalence function calculates this measure.

Usage

```
prevalence(obs, event = 1)
```

Arguments

obs	a vector of binary observations (e.g. 1 vs. 0, male vs. female, disease vs. no disease, etc.).
event	the value whose prevalence we want to calculate (e.g. 1, "present", etc.).

Value

Numeric value of the prevalence of `event` in the `obs` vector.

Author(s)

A. Marcia Barbosa

References

Barbosa A.M., Real R., Munoz A.R. & Brown J.A. (2013) New measures for assessing model equilibrium and prediction mismatch in species distribution models. Diversity and Distributions, in press

Jimenez-Valverde A. & Lobo J.M. (2006) The ghost of unbalanced species distribution data in geographical model predictions. Diversity and Distributions, 12: 521-524.

See Also

`evenness`

Examples

```
(x <- rep(c(0, 1), each = 5))

(y <- c(rep(0, 3), rep(1, 7)))

(z <- c(rep(0, 7), rep(1, 3)))

prevalence(x)

prevalence(y)

prevalence(z)
```

---

range01 *Shrink or stretch a vector to make it range between 0 and 1*

Description

This function re-scales a numeric vector so that it ranges between 0 and 1 (i.e., the lowest value becomes 0, the highest becomes 1, and the ones in the middle retain their rank and relative diference).

Usage

```
range01(x, na.rm = TRUE)
```

Arguments

`x`	a numeric vector.
`na.rm`	logical, whether to remove `NA` values.

Details

This function was borrowed from http://stackoverflow.com/questions/5468280/scale-a-series-between-two-points-in-r/5468527#5468527 and adapted to handle also missing values.

Value

A numeric vector of the same length as the input, now with the values ranging from 0 to 1.

Author(s)

A. Marcia Barbosa

See Also

standard01

Examples

```
range01(0:10)

range01(-12.3 : 21.7)
```

---

rotif.mods *Rotifer distribution models*

Description

A set of generalized linear models of rotifer species distributions on TDWG level 4 regions of the world (Fontaneto et al. 2012), together with their predicted values. Mind that these models are provided just as sample data and have limited application, due to limitations in the underlying distribution records. See Details for more information.

Usage

```
data(rotif.mods)
```

Format

A list of 2 elements:

$ predictions: a data.frame with 291 observations of 60 variables, namely the presence probability (P) and environmental favourability (F) for each of 30 species of rotifers, obtained from the rotif.env dataset in the **fuzzySim** package

$ models: a list of the 30 generalized linear model (link{glm}) objects which generated those predictions.

Details

These models were obtained with the `multGLM` function and the `rotif.env` dataset from package **fuzzySim**, using the following code:

```
require(fuzzySim) data(rotif.env) rotif.mods <- multGLM(data = rotif.env, sp.cols = 18:47, var.cols = 5
```

See package **fuzzySim** (currently available on R-Forge at http://fuzzysim.r-forge.r-project.org) for more information on the source data that were used to build these models.

References

Fontaneto D., Barbosa A.M., Segers H. & Pautasso M. (2012) The 'rotiferologist' effect and other global correlates of species richness in monogonont rotifers. Ecography, 35: 174-182.

Examples

```
data(rotif.mods)
head(rotif.mods$predictions)
rotif.mods$models[[1]]
```

RsqGLM *R-squared measures for GLMs*

Description

This function calculates some (pseudo) R-squared statistics for binomial Generalized Linear Models.

Usage

```
RsqGLM(model = NULL, obs = NULL, pred = NULL)
```

Arguments

`model`	a model object of class "glm".
`obs`	a vector of observed presences (1) and absences (0) or another binary response variable. Not necessary (and ignored) if `model` is provided.
`pred`	a vector with the corresponding predicted values of presence probability. Must be of the same length and in the same order as `obs`. Not necessary (and ignored) if `model` is provided.

Details

Implemented measures include the R-squareds of McFadden (1974), Cox-Snell (1989), Nagelkerke (1991, which corresponds to the corrected Cox-Snell, eliminating its upper bound), and Tjur (2009). See Allison (2014) for a brief review of these measures.

Value

The function returns a named list of the calculated R-squared values.

Note

Tjur's R-squared can only be calculated for models with binomial response variable; otherwise, NA will be returned.

Author(s)

A. Marcia Barbosa

References

Allison P. (2014) Measures of fit for logistic regression. SAS Global Forum, Paper 1485-2014

Cox, D.R. & Snell E.J. (1989) The Analysis of Binary Data, 2nd ed. Chapman and Hall, London

McFadden, D. (1974) Conditional logit analysis of qualitative choice behavior. In: Zarembka P. (ed.) Frontiers in Economics. Academic Press, New York

Nagelkerke, N.J.D. (1991) A note on a general definition of the coefficient of determination. Biometrika, 78: 691-692

Tjur T. (2009) Coefficients of determination in logistic regression models - a new proposal: the coefficient of discrimination. The American Statistician, 63: 366-372.

See Also

Dsquared, AUC, threshMeasures, HLfit

Examples

```
# load sample models:
data(rotif.mods)

# choose a particular model to play with:
mod <- rotif.mods$models[[1]]

RsqGLM(model = mod)


# you can also use RsqGLM with vectors of observed and predicted values
# instead of a model object:

RsqGLM(obs = mod$y, pred = mod$fitted.values)
```

`standard01` *Standardize to 0-1 (or vice-versa)*

Description

This function converts the score of a measure that ranges from -1 to 1 (e.g. a kappa or TSS value obtained for a model) into its (linearly) corresponding value in 0-to-1 scale, so that it can be compared directly with measures that range between 0 and 1 (such as CCR or AUC). It can also perform the conversion in the opposite direction.

Usage

```
standard01(score, direction = c("-1+1to01", "01to-1+1"))
```

Arguments

`score`	numeric value indicating the score of the measure of interest.
`direction`	character value indicating the direction in which to perform the standardization. The default, `"-1+1to01"`, can be switched to `"01to-1+1"`.

Details

While most of the threshold-based measures of model evaluation range theoretically from 0 to 1, some of them (such as Cohen's kappa and the true skill statistic, TSS) may range from -1 to 1 (Allouche et al. 2006). Thus, the values of different measures may not be directly comparable (Barbosa 2015). We do not usually get negative values of TSS or kappa (nor values under 0.5 for CCR or AUC, for example) because that only happens when model predictions perform worse than random guesses; still, such values are mathematically possible, and can occur e.g. when extrapolating models to regions where where the species-environment relationships differ. This standardization is included as an option in the `threshMeasures` function.

Value

The numeric value of `score` when re-scaled to the 0-to-1 (or to the -1 to +1) scale.

Note

Note that this is not the same as re-scaling a vector so that it ranges between 0 and 1, which is done by `range01`.

Author(s)

A. Marcia Barbosa

References

Allouche O., Tsoar A. & Kadmon R. (2006) Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). Journal of Applied Ecology 43: 1223-1232

Barbosa, A.M. (2015) Re-scaling of model evaluation measures to allow direct comparison of their values. The Journal of Brief Ideas, 18 Feb 2015, DOI: 10.5281/zenodo.15487

See Also

threshMeasures, range01

Examples

```
standard01(0.6)

standard01(0.6, direction = "-1+1to01")

standard01(0.6, direction = "01to-1+1")
```

---

threshMeasures *Threshold-based measures of model evaluation*

Description

This function calculates a number of measures for evaluating the discrimination capacity of a species distribution (or ecological niche, or bioclimatic envelope...) model against observed presence-absence data (Fielding & Bell 1997; Liu et al. 2011; Barbosa et al. 2013).

Usage

```
threshMeasures(model = NULL, obs = NULL, pred = NULL, thresh = 0.5,
measures = modEvAmethods("threshMeasures"), simplif = FALSE, plot = TRUE,
plot.ordered = FALSE, standardize = TRUE, messages = TRUE, ...)
```

Arguments

model	a model object of class "glm".
obs	a vector of observed presences (1) and absences (0) or another binary response variable. Not necessary (and ignored) if model is provided.
pred	a vector with the corresponding predicted values of presence probability, habitat suitability, environmental favourability or alike. Not necessary (and ignored) if model is provided.
thresh	numeric value of the threshold to separate predicted presences from predicted absences in pred; can be "preval", to use the prevalence of obs as the threshold, or any real number between 0 and 1. The default is 0.5 (but see Details).
measures	character vector of the evaluation measures to use. By default, all measures available in modEvAmethods("threshMeasures") are calculated.

simplif	logical, whether to calculate a faster, simplified version. Used internally by other functions in the package. Defaults to FALSE.
plot	logical, whether to produce a barplot of the calculated measures. Defaults to TRUE.
plot.ordered	logical, whether to plot the measures in decreasing order rather than in input order. Defaults to FALSE.
standardize	logical, whether to change measures that may range between -1 and +1 (namely kappa and TSS) to their corresponding value in the 0-to-1 scale (skappa and sTSS), so that they can compare directly to other measures (see standard01). The default is TRUE, but a message is displayed to inform the user about it.
messages	logical, whether to display messages.
...	additional arguments to be passed to the plot function.

Details

By default the threshold used is 0.5, but you may want to change this depending on a number of criteria (see e.g. Jimenez-Valverde & Lobo 2007, Nenzen & Araujo 2011). You can set thresh to "preval" (species' prevalence or proportion of presences in the input data), or calculate optimal threshold values according to different criteria with the optiThresh function. If you're using "environmental favourability" as input pred data (Real et al. 2006; see Fav function in package **fuzzySim**), then the 0.5 threshold corresponds to species prevalence.

While most of these threshold-based measures range from 0 to 1, some of them (such as kappa and TSS) may range from -1 to 1 (Allouche et al. 2006), so their raw scores are not directly comparable. threshMeasures includes an option (used by default) to standardize these measures to 0-1 (Barbosa 2015) using the standard01 function, so that you obtain the standardized versions skappa and sTSS.

This function can also be used to calculate the agreement between different presence-absence (or other types of binary) data, as e.g. Barbosa et al. (2012) did for comparing mammal distribution data from atlas and range maps. Notice, however, that some of these measures, such as TSS or NMI, are not symmetrical (obs vs. pred is different from pred vs. obs).

Value

If simplif = TRUE, the output is a numeric matrix with the name and value of each measure. If simplif = FALSE (the default), the ouptut is a bar plot of the calculated measures and a list with the following components:

N	the number of observations (records) in the analysis.
Prevalence	the prevalence (proportion of presences) in obs.
Threshold	the threshold value used to calculate the measures.
ConfusionMatrix	the confusion matrix obtained with the used threshold.
ThreshMeasures	a numeric matrix with the name and value of each measure.

Note

Some of these measures (like NMI, UPR, OPR, PPP, NPP) cannot be calculated for thresholds at which there are zeros in the confusion matrix.

Author(s)

A. Marcia Barbosa

References

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Barbosa A.M., Real R., Munoz A.R. & Brown J.A. (2013) New measures for assessing model equilibrium and prediction mismatch in species distribution models. Diversity and Distributions 19: 1333-1338

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Nenzen H.K. & Araujo M.B. (2011) Choice of threshold alters projections of species range shifts under climate change. Ecological Modelling 222: 3346-3354

Real R., Barbosa A.M. & Vargas J.M. (2006) Obtaining environmental favourability functions from logistic regression. Environmental and Ecological Statistics 13: 237-245.

See Also

optiThresh, optiPair, AUC, HLfit

Examples

```
# load sample models:
data(rotif.mods)

# choose a particular model to play with:
mod <- rotif.mods$models[[1]]

threshMeasures(model = mod, simplif = TRUE)

threshMeasures(model = mod)

threshMeasures(model = mod, plot.ordered = TRUE)

threshMeasures(model = mod, measures = c("CCR", "TSS", "kappa"))

threshMeasures(model = mod, plot.ordered = TRUE, thresh = "preval")
```

```
# you can also use threshMeasures with vectors of observed and predicted values
# instead of with a model object:

threshMeasures(obs = mod$y, pred = mod$fitted.values)
```

`varPart` *Variation partitioning*

Description

This function performs variation partitioning (Borcard et al. 1992) among two factors (e.g. Ribas et al. 2006) or three factors (e.g. Real et al. 2003) for either multiple linear regression models (LM) or generalized linear models (GLM).

Usage

```
varPart(A, B, C = NULL, AB, AC = NULL, BC = NULL, ABC = NULL, model.type,
A.name = "A", B.name = "B", C.name = "C", plot = TRUE, plot.digits = 3,
cex.names = 1.2, cex.values = 1)
```

Arguments

`A`	numeric value of the R-squared of the regression of the response variable on the variables related to factor 'A'
`B`	numeric value of the R-squared of the regression of the response variable on the variables related to factor 'B'
`C`	(optionally, if there are 3 factors) numeric value of the R-squared of the regression of the response on the variables related to factor 'C'
`AB`	numeric value of the R-squared of the regression of the response on the variables of factors 'A' and 'B' simultaneously
`AC`	(if there are 3 factors) numeric value of the R-squared of the regression of the response on the variables of factors 'A' and 'C' simultaneously
`BC`	(if there are 3 factors) numeric value of the R-squared of the regression of the response on the variables of factors 'B' and 'C' simultaneously
`ABC`	(if there are 3 factors) numeric value of the R-squared of the regression of the response on the variables of factors 'A', 'B' and 'C' simultaneously
`model.type`	character value, either "LM" (linear model) or "GLM" (generalised linear model) depending on your model type.
`A.name`	optional character indicating the name of factor 'A'
`B.name`	optional character indicating the name of factor 'B'
`C.name`	optional character indicating the name of factor 'C' (if there are 3 factors)
`plot`	logical, whether to plot the variation partitionig diagram.

plot.digits	integer value of the number of digits to which to round the values in the plot.
cex.names	numeric value indicating character expansion factor to define the size of the names of the factors displayed in the plot.
cex.values	numeric value indicating character expansion factor to define the size of the values displayed in the plot.

Details

If you have linear models, input data for varPart are the coefficients of determination (R-squared values) of the linear regressions of the target variable on all the variables in the model, on the variables related to each particular factor, and (when there are 3 factors) on the variables related to each pair of factors. The outputs are the amounts of variance explained exclusively by each factor, the amounts explained exclusively by the overlapping effects of each pair of factors, and the amount explained by the overlap of the 3 factors if this is the case (e.g. Real et al. 2003). The amount of variation not explained by the complete model is also provided.

If you have generalized linear models (GLMs) such as logistic regression (see glm), you have no R-squared values from these models; inputs are then the squared coefficients of (Spearman's) correlation between the model predictions given by each factor or pair of factors and the predictions of the complete model (e.g. Munoz & Real 2006), or the R-squared values of the corresponding logit (y) functions (Real et al. 2013), or an adjusted R-squared (De Araujo et al. 2013). Consequently, output values are not the total amounts of variance (of the target variable) explained by factors and overlaps, but rather their proportional contribution to the total variation explained by the model. The amount of unexplained variation is not available for GLMs.

Value

The output consists of a data frame indicating the proportion of variance accounted for by each of the factors, and (if plot = TRUE a Venn diagram of the contributions of each factor.)

Note

This function had a bug up to modEvA version 0.8: a line break prevented the ABC overlap from being calculated correctly. Thanks to Jurica Levatic for pointing this out and helping to solve it!

Author(s)

A. Marcia Barbosa

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Ribas, A., Barbosa, A.M., Casanova, J.C., Real, R., Feliu, C. & Vargas, J.M. (2006) Geographical patterns of the species richness of helminth parasites of moles (Talpa spp.) in Spain: separating the effect of sampling effort from those of other conditioning factors. Vie et Milieu 56: 1-8.

Examples

```
varPart(A = 0.857537, B = 0.078095, C = 0.499474, AB = 0.89933, BC = 0.492119,
AC = 0.981672, model.type = "GLM", A.name = "Climatic", B.name = "Human",
C.name = "Topographic", plot.digits = 3, cex.names = 1.2, cex.values = 1)
```

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