

Package ‘Distance’

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Maintainer Laura Marshall <lhm@st-andrews.ac.uk>

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Title Distance Sampling Detection Function and Abundance Estimation

LazyLoad yes

Author David Lawrence Miller

Description A simple way of fitting detection functions to distance sampling data for both line and point transects. Adjustment term selection, left and right truncation as well as monotonicity constraints and binning are supported. Abundance and density estimates can also be calculated (via a Horvitz-Thompson-like estimator) if survey area information is provided.

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URL <http://github.com/DistanceDevelopment/Distance/>

BugReports <https://github.com/DistanceDevelopment/Distance/issues>

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Distance-package *Distance sampling*

Description

Distance is a simple way to fit detection functions and estimate abundance using distance sampling methodology.

Details

Underlying Distance is the package `mrds`, for more advanced analyses (such as those involving double observer surveys) one may find it necessary to use `mrds`.

Examples of distance sampling analyses are available at <http://examples.distancesampling.org/>.

For help with distance sampling and this package, there is a Google Group <https://groups.google.com/forum/#!forum/distance-sampling>.

Author(s)

David L. Miller <dave@ninepointeightone.net>

References

Key References:

Miller D.L., E. Rexstad, L. Thomas, L. Marshall and J.L. Laake. 2019. Distance Sampling in R. *Journal of Statistical Software*, 89(1), 1-28. <http://doi.org/10.18637/jss.v089.i01>.

Background References:

Laake, J.L. and D.L. Borchers. 2004. Methods for incomplete detection at distance zero. In: *Advanced Distance Sampling*, eds. S.T. Buckland, D.R. Anderson, K.P. Burnham, J.L. Laake, D.L. Borchers, and L. Thomas. Oxford University Press.

Marques, F.F.C. and S.T. Buckland. 2004. Covariate models for the detection function. In: *Advanced Distance Sampling*, eds. S.T. Buckland, D.R. Anderson, K.P. Burnham, J.L. Laake, D.L. Borchers, and L. Thomas. Oxford University Press.

`add_df_covar_line` *Add covariate levels detection function plots*

Description

Add a line or lines to a plot of the detection function which correspond to a given covariate combination. These can be particularly useful when there is a small number of factor levels or if quantiles of a continuous covariate are specified.

Arguments

ddf	a fitted detection function object
data	a data.frame with the covariate combination you want to plot
...	extra arguments to give to <code>line</code> (lty, lwd, col)
ndist	number of points to evaluate the detection function at

Details

All covariates must be specified in `data`. Plots can become quite busy when this approach is used. It may be useful to fix some covariates at their median level and plot set values of a covariate of interest. For example setting weather (e.g., Beaufort) to its median and plotting levels of observer, then creating a second plot for a fixed observer with levels of weather.

Arguments to `lines` are supplied in `...` and aesthetics like line type (`lty`), line width (`lwd`) and colour (`col`) are recycled. By default `lty` is used to distinguish between the lines. It may be useful to add a `legend` to the plot (lines are plotted in the order of `data`).

Value

invisibly, the values of detectability over the truncation range

Note

This function is located in the `mrds` package but the documentation is provided here for easy access.

Author(s)

David L Miller

Examples

```
## Not run:
# example using a model for the minke data
data(minke)
# fit a model
result <- ds(minke, formula=~Region.Label)

# make a base plot, showpoints=FALSE makes the plot less busy
plot(result, showpoints=FALSE)

# add lines for sex one at a time
add_df_covar_line(result, data.frame(Region.Label="South"), lty=2)
add_df_covar_line(result, data.frame(Region.Label="North"), lty=3)

# add a legend
legend(1.5, 1, c("Average", "South", "North"), lty=1:3)

## End(Not run)
```

`AIC.dsmodel`*Akaike's An Information Criterion for detection functions*

Description

Extract the AIC from a fitted detection function.

Usage

```
## S3 method for class 'dsmodel'  
AIC(object, ..., k = 2)
```

Arguments

<code>object</code>	a fitted detection function object
<code>...</code>	optionally more fitted model objects.
<code>k</code>	penalty per parameter to be used; the default <code>k = 2</code> is the "classical" AIC

Author(s)

David L Miller

Examples

```
## Not run:  
library(Distance)  
data(minke)  
model <- ds(minke, truncation=4)  
model_hr <- ds(minke, truncation=4, key="hr")  
# extract the AIC for 2 models  
AIC(model, model_hr)  
  
## End(Not run)
```

`amakihi`*Hawaiian amakihi point transect data*

Description

Also known as the Common 'Amakihi, a type of Hawaiian honeycreeper

Format

A data frame with 1487 rows and 12 variables

Region.Label	strata names (seven strata)
Area	size of study area (set to 0)
Sample.Label	transect ID
Effort	number of visits to point
object	object ID
distance	radial distance (m)
Month	month survey conducted (not used)
OBS	observer ID (note capitalisation of variable name)
Sp	species code (COAM) for all detections
MAS	Time after sunrise (min)
HAS	Time after sunrise (hours)
Study.Area	name of study area

Note

Example for investigating covariates in the detection function. Note high collinearity between two measures of time since sunrise. Convergence problems can result from models with several factor covariates.

References

Marques, T.A., L. Thomas, S.G. Fancy and S.T. Buckland. (2007) Improving estimates of bird density using multiple-covariate distance sampling. *The Auk* 124 (4): 1229–1243. [https://doi.org/10.1642/0004-8038\(2007\)124\[1229:IEOBDU\]2.0.CO;2](https://doi.org/10.1642/0004-8038(2007)124[1229:IEOBDU]2.0.CO;2).

 bootdht

Bootstrap uncertainty estimation for distance sampling models

Description

Performs a bootstrap for simple distance sampling models using the same data structures as [dht](#).

Usage

```
bootdht(
  model,
  flatfile,
  resample_strata = FALSE,
  resample_obs = FALSE,
  resample_transects = TRUE,
  nboot = 100,
  summary_fun = bootdht_Nhat_summarize,
  convert.units = 1,
```

```

    select_adjustments = FALSE,
    sample_fraction = 1
)

```

Arguments

<code>model</code>	a model fitted by <code>ds</code> or a list of models
<code>flatfile</code>	Data provided in the flatfile format. See flatfile for details.
<code>resample_strata</code>	should resampling happen at the stratum (<code>Region.Label</code>) level? (Default FALSE)
<code>resample_obs</code>	should resampling happen at the observation (object) level? (Default FALSE)
<code>resample_transects</code>	should resampling happen at the transect (<code>Sample.Label</code>) level? (Default TRUE)
<code>nboot</code>	number of bootstrap replicates
<code>summary_fun</code>	function that is used to obtain summary statistics from the bootstrap, see Summary Functions below. By default <code>bootdht_Nhat_summarize</code> is used, which just extracts abundance estimates.
<code>convert.units</code>	conversion between units for abundance estimation, see "Units", below. (Defaults to 1, implying all of the units are "correct" already.) This takes precedence over any unit conversion stored in <code>model</code> .
<code>select_adjustments</code>	select the number of adjustments in each bootstrap, when FALSE the exact detection function specified in <code>model</code> is fitted to each replicate. Setting this option to TRUE can significantly increase the runtime for the bootstrap. Note that for this to work <code>model</code> must have been fitted with <code>adjustment!=NULL</code> .
<code>sample_fraction</code>	what proportion of the transects was covered (e.g., 0.5 for one-sided line transects).

Summary Functions

The function `summary_fun` allows the user to specify what summary statistics should be recorded from each bootstrap. The function should take two arguments, `ests` and `fit`. The former is the output from `dht2`, giving tables of estimates. The latter is the fitted detection function object. The function is called once fitting and estimation has been performed and should return a `data.frame`. Those `data.frames` are then concatenated using `rbind`. One can make these functions return any information within those objects, for example abundance or density estimates or the AIC for each model. See Examples below.

Model selection

Model selection can be performed on a per-replicate basis within the bootstrap. This has three variations:

1. when `select_adjustments` is TRUE then adjustment terms are selected by AIC within each bootstrap replicate (provided that `model` had the order and adjustment options set to non-NULL).

2. if `model` is a list of fitted detection functions, each of these is fitted to each replicate and results generated from the one with the lowest AIC.
3. when `select_adjustments` is TRUE and `model` is a list of fitted detection functions, each model fitted to each replicate and number of adjustments is selected via AIC.

The last of these options can be very time consuming!

See Also

[summary.dht_bootstrap](#) for how to summarize the results, [bootdht_Nhat_summarize](#) for an example summary function.

Examples

```
## Not run:
# fit a model to the minke data
data(minke)
mod1 <- ds(minke)

# summary function to save the abundance estimate
Nhat_summarize <- function(ests, fit) {
  return(data.frame(Nhat=ests$individuals$N$Estimate))
}

# perform 5 bootstraps
bootout <- bootdht(mod1, flatfile=minke, summary_fun=Nhat_summarize, nboot=5)

# obtain basic summary information
summary(bootout)

## End(Not run)
```

bootdht_Nhat_summarize

Simple summary for bootstrap model

Description

When using [bootdht](#) one needs to use a summary function to extract results from the resulting models per replicate. This function is the simplest possible example of such a function, that just extracts the estimated abundance. Further examples of such functions can be found at <http://examples.distancesampling.org>.

Usage

```
bootdht_Nhat_summarize(ests, fit)
```


Arguments

ests	output from dht2 .
fit	fitted detection function object (unused).

Value

data.frame with one column ("Nhat"), containing estimate(s) of abundance of individuals from each bootstrap replicate. This data frame can be examined for example, with `quantile` to compute confidence intervals.

See Also

[bootdht](#), which this function is to be used with.

capercaillie	<i>Capercaillie in Monaughty Forest</i>
--------------	---

Description

Data from a line transect survey of capercaillie in Monaughty Forest, Moray, Scotland.

Format

A data frame with 112 observations on the following 9 variables.

Sample.Label	name of single transect
Effort	transect length (km)
distance	perpendicular distance (m)
object	object ID
size	only individual birds detected
detected	whether detected
observer	single observer data
Region.Label	stratum name
Area	size of Monaughty Forest (ha)

checkdata	<i>Check that the data supplied to ds is correct</i>
-----------	--

Description

This is an internal function that checks the data.frames supplied to ds are "correct".

Usage

```

checkdata(
  data,
  region.table = NULL,
  sample.table = NULL,
  obs.table = NULL,
  formula = ~1
)

```

Arguments

data	as in ds
region.table	as in ds
sample.table	as in ds
obs.table	as in ds
formula	formula for the covariates

Value

Throws an error if something goes wrong, otherwise returns a data.frame.

Author(s)

David L. Miller

ClusterExercise

Simulated minke whale data with cluster size

Description

Data simulated from models fitted to 1992/1993 Southern Hemisphere minke whale data collected by the International Whaling Commission. See Branch and Butterworth (2001) for survey details (survey design is shown in figure 1(e)). Data simulated by David Borchers.

Format

data.frame with 99 observations of 9 variables:

Region.Label	stratum label ("North" or "South")
Area	stratum area (square nautical mile)
Sample.Label	transect identifier
Effort	transect length (nautical mile)
distance	observed distance (nautical mile)
Cluster.strat	strata based on cluster size: 1, 2 and 3+
size	cluster size
Study.Area	name of study area

References

- Branch, T.A. and D.S. Butterworth. (2001) Southern Hemisphere minke whales: standardised abundance estimates from the 1978/79 to 1997/98 IDCR-SOWER surveys. *Journal of Cetacean Research and Management* 3(2): 143-174
- Hedley, S.L., and S.T. Buckland. (2004) Spatial models for line transect sampling. *Journal of Agricultural, Biological, and Environmental Statistics* 9: 181-199. doi:10.1198/1085711043578.

convert_units	<i>Convert units for abundance estimation</i>
---------------	---

Description

It is often the case that effort, distances and prediction area are collected in different units in the field. Functions in `Distance` allow for an argument to convert between these and provide an answer that makes sense. This function calculates that conversion factor, given knowledge of the units of the quantities used.

Usage

```
convert_units(distance_units, effort_units, area_units)
```

Arguments

`distance_units` units distances were measured in.

`effort_units` units that effort were measured in. Set as NULL for point transects.

`area_units` units for the prediction area.

Details

`convert_units` expects particular names for its inputs – these should be singular names of the unit (e.g., "metre" rather than "metres"). You can view possible options with `units_table`. Both UK and US spellings are acceptable, case does not matter. For density estimation, area must still be provided ("objects per square ???"). Note that for cue counts (or other multiplier-based methods) one will still have to ensure that the rates are in the correct units for the survey.

Author(s)

David L Miller

Examples

```
# distances measured in metres, effort in kilometres and
# abundance over an area measured in hectares:
convert_units("Metre", "Kilometre", "Hectare")

# all SI units, so the result is 1
convert_units("Metre", "metre", "square metre")
```

```
# for points ignore effort
convert_units("Metre", NULL, "Hectare")
```

```
create.bins          Create bins from a set of binned distances and a set of cutpoints.
```

Description

This is an internal routine and shouldn't be necessary in normal analyses.

Usage

```
create.bins(data, cutpoints)
```

Arguments

```
data          data.frame with at least the column distance.
cutpoints     vector of cutpoints for the bins
```

Value

data data with two extra columns distbegin and distend.

Author(s)

David L. Miller

Examples

```
## Not run:
library(Distance)
data(minke)

# put the minke data into bins 0-1, 1-2, 2-3 km
minke_cuts <- create.bins(minke[!is.na(minke$distance),], c(0,1,2,3))

## End(Not run)
```

```
CueCountingExample  Cue counts of whale blows
```

Description

Cues are treated as an indirect count, requiring the use of multipliers.

Format

A data frame with 109 rows and 15 variables.

Region.Label	stratum labels
Area	size (km ²) of each stratum
Sample.Label	transect labels
Cue.rate	rate of blows per animal per hour
Cue.rate.SE	variability in cue rate
Cue.rate.df	degrees of freedom (number of animals sampled for cues)
object	object ID
distance	perpendicular distance (km)
Sample.Fraction	proportion of full circle scanned (radians)
Sample.Fraction.SE	variability in sampling fraction (0)
Search.time	Duration of scanning effort (hr)
bss	Beaufort sea state
sp	Species detected (all observations W in these data)
size	Number of animals in group (all 1 in these data)
Study.Area	study area name

Details

Because whale blows disappear instantaneously, there is no need to measure a decay rate. However a cue production rate (blows per individual per unit time) is required, as is a measure of variability of that rate.

Note

There are two other nuances in this survey. Even though the survey is taking place on a moving ship, effort is measured as amount of time scanning for blows. In some instances, it is not possible for the observer to scan the sea all around them as view may be restricted by the ship's superstructure. Here a sampling fraction multiplier is employed to deal with restricted vision. Units of measure of cue.rate and Search.time must be equal.

dht2

Abundance estimation for distance sampling models

Description

Once a detection function is fitted to data, this function can be used to compute abundance estimates over required areas. The function also allows for stratification and variance estimation via various schemes (see below).

Usage

```
dht2(
  ddf,
  observations = NULL,
  transects = NULL,
  geo_strat = NULL,
```

```

flatfile = NULL,
strat_formula,
convert_units = 1,
er_est = c("R2", "P2"),
multipliers = NULL,
sample_fraction = 1,
ci_width = 0.95,
innes = FALSE,
stratification = "geographical",
total_area = NULL,
binomial_var = FALSE
)

```

Arguments

<code>ddf</code>	model fitted by <code>ds</code> or <code>ddf</code>
<code>observations</code>	<code>data.frame</code> to link detection function data (indexed by object column IDs) to the transects (indexed by <code>Sample.Label</code> column IDs). See "Data" below.
<code>transects</code>	<code>data.frame</code> with information about samples (points or line transects). See "Data" below.
<code>geo_strat</code>	<code>data.frame</code> with information about any geographical stratification. See "Data" below.
<code>flatfile</code>	data in the flatfile format, see flatfile .
<code>strat_formula</code>	a formula giving the stratification structure (see "Stratification" below). Currently only one level of stratification is supported.
<code>convert_units</code>	conversion factor between units for the distances, effort and area. See "Units" below.
<code>er_est</code>	encounter rate variance estimator to be used. See "Variance" below and varn .
<code>multipliers</code>	list of <code>data.frames</code> . See "Multipliers" below.
<code>sample_fraction</code>	what proportion of the transects was covered (e.g., 0.5 for one-sided line transects).
<code>ci_width</code>	for use with confidence interval calculation (defined as 1-alpha, so the default 95 will give a 95% confidence interval).
<code>innes</code>	logical flag for computing encounter rate variance using either the method of Innes et al (2002) where estimated abundance per transect divided by effort is used as the encounter rate, vs. (when <code>innes=FALSE</code>) using the number of observations divided by the effort (as in Buckland et al., 2001)
<code>stratification</code>	what do strata represent, see "Stratification" below.
<code>total_area</code>	for options <code>stratification="effort_sum"</code> and <code>stratification="replicate"</code> the area to use as the total for combined, weighted final estimates.
<code>binomial_var</code>	if we wish to estimate abundance for the covered area only (i.e., study area = surveyed area) then this must be set to be TRUE and use the binomial variance estimator of Borchers et al. (1998). This is only valid when objects are not clustered. (This situation is rare.)

Value

a `data.frame` with estimates and attributes containing additional information

Data

The data format allows for complex stratification schemes to be set-up. Before going into this detail, three objects are always required:

ddf the detection function (see `Distance::ds` or `mrds::ddf` for information on the format of their inputs).

`observations` has one row per observation and links the observations to the transects. Required columns: `object` (unique ID for the observation, which must match with the data in the detection function) and `Sample.Label` (unique ID for the transect). Additional columns for strata which are not included in the detection function are required (stratification covariates that are included in the detection function do not need to be included here). The important case here is group size, which must have column name `size` (but does not need to be in the detection function).

`transects` has one row per sample (point or line transect). At least one row is required. Required columns: `Sample.Label` (unique ID for the transect), `Effort` (line length for line transects, number of visits for point transects), if there is more than one geographical stratum.

With only these three arguments, abundance can only be calculated for the covered area. Including additional information on the area we wish to extrapolate to (i.e., the study area), we can obtain abundance estimates:

`geo_strat` has one row for each stratum that we wish to estimate abundance for. For abundance in the study area, at least one row is required. Required columns: `Area` (the area of that stratum). If there is >1 row, then additional columns, named in `strat_formula`.

Multipliers

It is often the case that we cannot measure distances to individuals or groups directly, but instead need to estimate distances to something they produce (e.g., for whales, their blows; for elephants their dung) – this is referred to as indirect sampling. We may need to use estimates of production rate and decay rate for these estimates (in the case of dung or nests) or just production rates (in the case of songbird calls or whale blows). We refer to these conversions between "number of cues" and "number of animals" as "multipliers". The `multipliers` argument is a list, with 2 possible elements (creation and decay) Each element of which is a `data.frame` and must have at least a column named `rate`, which abundance estimates will be divided by (the term "multiplier" is a misnomer, but kept for compatibility with `Distance for Windows`). Additional columns can be added to give the standard error and degrees of freedom for the rate if known as `SE` and `df`, respectively.

Stratification

The `strat_formula` argument is used to specify a column to use to stratify the results, using the form `~column.name` where `column.name` is the column name you wish to use.

The `stratification` argument is used to specify which of four types of stratification are intended:

"geographical" if each stratum represents a different geographical areas and you want the total over all the areas

"effort_sum" if your strata are in fact from replicate surveys (perhaps using different designs) but you don't have many replicates and/or want an estimate of "average variance".

"replicate" if you have replicate surveys but have many of them, this calculates the average abundance and the variance between those many surveys (think of a population of surveys)

"object" if the stratification is really about the type of object observed, for example sex, species or life stage and what you want is the total number of individuals across all the classes of objects. For example, if you have stratified by sex and have males and females, but also want a total number of animals, you should use this option.

A simple example of using stratification="geographical" is given below. Further examples can be found at <http://examples.distancesampling.org/> (see, e.g., the deer pellet survey).

Variance

Variance in the estimated abundance comes from multiple sources. Depending on the data used to fit the model and estimate abundance, different components will be included in the estimated variances. In the simplest case, the detection function and encounter rate variance need to be combined. If group size varies, then this too must be included. Finally, if multipliers are used and have corresponding standard errors given, this are also included. Variances are combined by assuming independence between the measures and adding variances. A brief summary of how each component is calculated is given here, though see references for more details.

detection function variance from the detection function parameters is transformed to variance about the abundance via a sandwich estimator (see e.g., Appendix C of Borchers et al (2002)).

encounter rate for strata with >1 transect in them, the encounter rate estimators given in Fewster et al (2009) can be specified via the `er_est` argument. If the argument `innes=TRUE` then calculations use the estimated number of individuals in the transect (rather than the observed), which was give by Innes et al (2002) as a superior estimator. When there is only one transect in a stratum, Poisson variance is assumed. Information on the Fewster encounter rate variance estimators are given in [varn](#)

group size if objects occur in groups (sometimes "clusters"), then the empirical variance of the group sizes is added to the total variance.

multipliers if multipliers with standard errors are given, their corresponding variances are added. If no standard errors are supplied, then their contribution to variance is assumed to be 0.

Units

It is often the case that distances are recorded in one convenient set of units, whereas the study area and effort are recorded in some other units. To ensure that the results from this function are in the expected units, we use the `convert_units` argument to supply a single number to convert the units of the covered area to those of the study/stratification area (results are always returned in the units of the study area). For line transects, the covered area is calculated as $2 * width * length$ where width is the effective (half)width of the transect (often referred to as w in the literature) and length is the line length (referred to as L). If width and length are measured in kilometres and the study area in square kilometres, then all is fine and `convert_units` is 1 (and can be ignored). If, for example, line length and distances were measured in metres, we instead need to convert this to be

kilometres, by dividing by 1000 for each of distance and length, hence `convert_units=1e-6`. For point transects, this is slightly easier as we only have the radius and study area to consider, so the conversion is just such that the units of the truncation radius are the square root of the study area units.

References

- Borchers, D.L., S.T. Buckland, P.W. Goedhart, E.D. Clarke, and S.L. Hedley. 1998. Horvitz-Thompson estimators for double-platform line transect surveys. *Biometrics* 54: 1221-1237.
- Borchers, D.L., S.T. Buckland, and W. Zucchini. 2002 *Estimating Animal Abundance: Closed Populations*. Statistics for Biology and Health. Springer London.
- Buckland, S.T., E.A. Rexstad, T.A. Marques, and C.S. Oedekoven. 2015 *Distance Sampling: Methods and Applications*. Methods in Statistical Ecology. Springer International Publishing.
- Buckland, S.T., D.R. Anderson, K. Burnham, J.L. Laake, D.L. Borchers, and L. Thomas. 2001 *Introduction to Distance Sampling: Estimating Abundance of Biological Populations*. Oxford University Press.
- Innes, S., M. P. Heide-Jorgensen, J.L. Laake, K.L. Laidre, H.J. Cleator, P. Richard, and R.E.A. Stewart. 2002 Surveys of belugas and narwhals in the Canadian high arctic in 1996. *NAMMCO Scientific Publications* 4, 169-190.

Examples

```
## Not run:
# example of simple geographical stratification
# minke whale data, with 2 strata: North and South
data(minke)
# first fitting the detection function
minke_df <- ds(minke, truncation=1.5, adjustment=NULL)
# now estimate abundance using dht2
# stratum labels are in the Region.Label column
minke_dht2 <- dht2(minke_df, flatfile=minke, stratification="geographical",
  strat_formula=~Region.Label)
# could compare this to minke_df$dht and see the same results
minke_dht2
# can alternatively report density
print(minke_dht2, report="density")

## End(Not run)
```

 ds

Fit detection functions and calculate abundance from line or point transect data

Description

This function fits detection functions to line or point transect data and then (provided that survey information is supplied) calculates abundance and density estimates. The examples below illustrate some basic types of analysis using `ds()`.

Usage

```

ds(
  data,
  truncation = ifelse(is.null(cutpoints), ifelse(is.null(data$distend),
    max(data$distance), max(data$distend)), max(cutpoints)),
  transect = c("line", "point"),
  formula = ~1,
  key = c("hn", "hr", "unif"),
  adjustment = c("cos", "herm", "poly"),
  order = NULL,
  scale = c("width", "scale"),
  cutpoints = NULL,
  dht.group = FALSE,
  monotonicity = ifelse(formula == ~1, "strict", "none"),
  region.table = NULL,
  sample.table = NULL,
  obs.table = NULL,
  convert.units = 1,
  er.var = "R2",
  method = "nlminb",
  quiet = FALSE,
  debug.level = 0,
  initial.values = NULL,
  max.adjustments = 5
)

```

Arguments

data	a data.frame containing at least a column called distance or a numeric vector containing the distances. NOTE! If there is a column called size in the data then it will be interpreted as group/cluster size, see the section "Clusters/groups", below. One can supply data as a "flat file" and not supply region.table, sample.table and obs.table, see "Data format", below and flatfile .
truncation	either truncation distance (numeric, e.g. 5) or percentage (as a string, e.g. "15%"). Can be supplied as a list with elements left and right if left truncation is required (e.g. list(left=1,right=20) or list(left="1%",right="15%") or even list(left="1",right="15%")). By default for exact distances the maximum observed distance is used as the right truncation. When the data is binned, the right truncation is the largest bin end point. Default left truncation is set to zero.
transect	indicates transect type "line" (default) or "point".
formula	formula for the scale parameter. For a CDS analysis leave this as its default ~1.
key	key function to use; "hn" gives half-normal (default), "hr" gives hazard-rate and "unif" gives uniform. Note that if uniform key is used, covariates cannot be included in the model.
adjustment	adjustment terms to use; "cos" gives cosine (default), "herm" gives Hermite polynomial and "poly" gives simple polynomial. "cos" is recommended. A

	value of NULL indicates that no adjustments are to be fitted.						
order	orders of the adjustment terms to fit (as a vector/scalar), the default value (NULL) will select via AIC up to <code>max.adjustments</code> adjustments. If a single number is given, that number is expanded to be <code>seq(term_min,order,by=1)</code> where <code>term_min</code> is the appropriate minimum order for this type of adjustment. For cosine adjustments, valid orders are integers greater than 2 (except when a uniform key is used, when the minimum order is 1). For Hermite polynomials, even integers equal or greater than 2 are allowed and for simple polynomials even integers equal or greater than 2 are allowed (though note these will be multiplied by 2, see Buckland et al, 2001 for details on their specification).						
scale	the scale by which the distances in the adjustment terms are divided. Defaults to "width", scaling by the truncation distance. If the key is uniform only "width" will be used. The other option is "scale": the scale parameter of the detection						
cutpoints	if the data are binned, this vector gives the cutpoints of the bins. Ensure that the first element is 0 (or the left truncation distance) and the last is the distance to the end of the furthest bin. (Default NULL, no binning.) Note that if data has columns <code>distbegin</code> and <code>distend</code> then these will be used as bins if cutpoints is not specified. If both are specified, cutpoints has precedence.						
dht.group	should density abundance estimates consider all groups to be size 1 (abundance of groups) <code>dht.group=TRUE</code> or should the abundance of individuals (group size is taken into account), <code>dht.group=FALSE</code> . Default is FALSE (abundance of individuals is calculated).						
monotonicity	should the detection function be constrained for monotonicity weakly ("weak"), strictly ("strict") or not at all ("none" or FALSE). See Monotonicity, below. (Default "strict"). By default it is on for models without covariates in the detection function, off when covariates are present.						
region.table	data.frame with two columns: <table border="0" style="margin-left: 40px;"> <tr> <td>Region.Label</td> <td>label for the region</td> </tr> <tr> <td>Area</td> <td>area of the region</td> </tr> </table> <p>region.table has one row for each stratum. If there is no stratification then region.table has one entry with Area corresponding to the total survey area. If Area is omitted density estimates only are produced.</p>	Region.Label	label for the region	Area	area of the region		
Region.Label	label for the region						
Area	area of the region						
sample.table	data.frame mapping the regions to the samples (i.e. transects). There are three columns: <table border="0" style="margin-left: 40px;"> <tr> <td>Sample.Label</td> <td>label for the sample</td> </tr> <tr> <td>Region.Label</td> <td>label for the region that the sample belongs to.</td> </tr> <tr> <td>Effort</td> <td>the effort expended in that sample (e.g. transect length).</td> </tr> </table>	Sample.Label	label for the sample	Region.Label	label for the region that the sample belongs to.	Effort	the effort expended in that sample (e.g. transect length).
Sample.Label	label for the sample						
Region.Label	label for the region that the sample belongs to.						
Effort	the effort expended in that sample (e.g. transect length).						
obs.table	data.frame mapping the individual observations (objects) to regions and samples. There should be three columns: <table border="0" style="margin-left: 40px;"> <tr> <td>object</td> <td>unique numeric identifier for the observation</td> </tr> </table>	object	unique numeric identifier for the observation				
object	unique numeric identifier for the observation						

Region.Label	label for the region that the sample belongs to.
Sample.Label	label for the sample
convert.units	conversion between units for abundance estimation, see "Units", below. (Defaults to 1, implying all of the units are "correct" already.)
er.var	encounter rate variance estimator to use when abundance estimates are required. Defaults to "R2" for line transects and "P3" for point transects. See dht2 for more information and if more complex options are required.
method	optimization method to use (any method usable by optim or optimx). Defaults to "nlminb".
quiet	suppress non-essential messages (useful for bootstraps etc). Default value FALSE.
debug.level	print debugging output. 0=none, 1-3 increasing levels of debugging output.
initial.values	a list of named starting values, see mrds-opt . Only allowed when AIC term selection is not used.
max.adjustments	maximum number of adjustments to try (default 5) only used when order=NULL.

Value

a list with elements:

ddf	a detection function model object.
dht	abundance/density information (if survey region data was supplied, else NULL).

Details

If abundance estimates are required then the `data.frames` `region.table` and `sample.table` must be supplied. If data does not contain the columns `Region.Label` and `Sample.Label` then the `data.frame` `obs.table` must also be supplied. Note that stratification only applies to abundance estimates and not at the detection function level.

For more advanced abundance/density estimation please see the [dht](#) and [dht2](#) functions.

Examples of distance sampling analyses are available at <http://examples.distancesampling.org/>.

Clusters/groups

Note that if the data contains a column named `size`, cluster size will be estimated and density/abundance will be based on a clustered analysis of the data. Setting this column to be `NULL` will perform a non-clustered analysis (for example if "size" means something else in your dataset).

Truncation

The right truncation point is by default set to be largest observed distance or bin end point. This is a default will not be appropriate for all data and can often be the cause of model convergence failures. It is recommended that one plots a histogram of the observed distances prior to model fitting so

as to get a feel for an appropriate truncation distance. (Similar arguments go for left truncation, if appropriate). Buckland et al (2001) provide guidelines on truncation.

When specified as a percentage, the largest right and smallest left percent distances are discarded. Percentages cannot be supplied when using binned data.

For left truncation, there are two options: (1) fit a detection function to the truncated data as is (this is what happens when you set left). This does not assume that $g(x)=1$ at the truncation point. (2) manually remove data with distances less than the left truncation distance – effectively move the centre line out to be the truncation distance (this needs to be done before calling ds). This then assumes that detection is certain at the left truncation distance. The former strategy has a weaker assumption, but will give higher variance as the detection function close to the line has no data to tell it where to fit – it will be relying on the data from after the left truncation point and the assumed shape of the detection function. The latter is most appropriate in the case of aerial surveys, where some area under the plane is not visible to the observers, but their probability of detection is certain at the smallest distance.

Binning

Note that binning is performed such that bin 1 is all distances greater or equal to cutpoint 1 (≥ 0 or left truncation distance) and less than cutpoint 2. Bin 2 is then distances greater or equal to cutpoint 2 and less than cutpoint 3 and so on.

Monotonicity

When adjustment terms are used, it is possible for the detection function to not always decrease with increasing distance. This is unrealistic and can lead to bias. To avoid this, the detection function can be constrained for monotonicity (and is by default for detection functions without covariates).

Monotonicity constraints are supported in a similar way to that described in Buckland et al (2001). 20 equally spaced points over the range of the detection function (left to right truncation) are evaluated at each round of the optimisation and the function is constrained to be either always less than it's value at zero ("weak") or such that each value is less than or equal to the previous point (monotonically decreasing; "strict"). See also [check.mono](#) in mrds.

Even with no monotonicity constraints, checks are still made that the detection function is monotonic, see [check.mono](#).

Units

In extrapolating to the entire survey region it is important that the unit measurements be consistent or converted for consistency. A conversion factor can be specified with the `convert.units` variable. The values of Area in `region.table`, must be made consistent with the units for Effort in `sample.table` and the units of distance in the `data.frame` that was analyzed. It is easiest if the units of Area are the square of the units of Effort and then it is only necessary to convert the units of distance to the units of Effort. For example, if Effort was entered in kilometres and Area in square kilometres and distance in metres then using `convert.units=0.001` would convert metres to kilometres, density would be expressed in square kilometres which would then be consistent with units for Area. However, they can all be in different units as long as the appropriate composite value for `convert.units` is chosen. Abundance for a survey region can be expressed as: $A*N/a$ where A is Area for the survey region, N is the abundance in the covered (sampled) region, and a is the area of the sampled region and is in units of Effort * distance. The sampled region a is multiplied

by `convert.units`, so it should be chosen such that the result is in the same units as `Area`. For example, if `Effort` was entered in kilometres, `Area` in hectares (100m x 100m) and distance in metres, then using `convert.units=10` will convert `a` to units of hectares (100 to convert metres to 100 metres for distance and `.1` to convert km to 100m units).

Data format

One can supply data only to simply fit a detection function. However, if abundance/density estimates are necessary further information is required. Either the `region.table`, `sample.table` and `obs.table` data.frames can be supplied or all data can be supplied as a "flat file" in the `data` argument. In this format each row in `data` has additional information that would ordinarily be in the other tables. This usually means that there are additional columns named: `Sample.Label`, `Region.Label`, `Effort` and `Area` for each observation. See [flatfile](#) for an example.

Density estimation

If column `Area` is omitted, a density estimate is generated but note that the degrees of freedom/standard errors/confidence intervals will not match density estimates made with the `Area` column present.

Author(s)

David L. Miller

References

- Buckland, S.T., Anderson, D.R., Burnham, K.P., Laake, J.L., Borchers, D.L., and Thomas, L. (2001). *Distance Sampling*. Oxford University Press. Oxford, UK.
- Buckland, S.T., Anderson, D.R., Burnham, K.P., Laake, J.L., Borchers, D.L., and Thomas, L. (2004). *Advanced Distance Sampling*. Oxford University Press. Oxford, UK.

See Also

[flatfile](#) [AIC.ds](#) [ds.gof](#) [p_dist_table](#) [plot.ds](#) [add_df_covar_line](#)

Examples

```
# An example from mrds, the golf tee data.
library(Distance)
data(book.tee.data)
tee.data<-book.tee.data$book.tee.dataframe[book.tee.data$book.tee.dataframe$observer==1, ]
ds.model <- ds(tee.data, 4)
summary(ds.model)
plot(ds.model)

## Not run:
# same model, but calculating abundance
# need to supply the region, sample and observation tables
region <- book.tee.data$book.tee.region
samples <- book.tee.data$book.tee.samples
obs <- book.tee.data$book.tee.obs
```

```

ds.dht.model <- ds(tee.data, 4, region.table=region,
                  sample.table=samples, obs.table=obs)
summary(ds.dht.model)

# specify order 2 cosine adjustments
ds.model.cos2 <- ds(tee.data, 4, adjustment="cos", order=2)
summary(ds.model.cos2)

# specify order 2 and 3 cosine adjustments, turning monotonicity
# constraints off
ds.model.cos23 <- ds(tee.data, 4, adjustment="cos", order=c(2, 3),
                   monotonicity=FALSE)
# check for non-monotonicity -- actually no problems
check.mono(ds.model.cos23$ddf, plot=TRUE, n.pts=100)

# include both a covariate and adjustment terms in the model
ds.model.cos2.sex <- ds(tee.data, 4, adjustment="cos", order=2,
                      monotonicity=FALSE, formula=~as.factor(sex))
# check for non-monotonicity -- actually no problems
check.mono(ds.model.cos2.sex$ddf, plot=TRUE, n.pts=100)

# truncate the largest 10% of the data and fit only a hazard-rate
# detection function
ds.model.hr.trunc <- ds(tee.data, truncation="10%", key="hr",
                      adjustment=NULL)
summary(ds.model.hr.trunc)

# compare AICs between these models:
AIC(ds.model)
AIC(ds.model.cos2)
AIC(ds.model.cos23)

## End(Not run)

```

ds.gof

Goodness of fit tests for distance sampling models

Description

Chi-square, Kolmogorov-Smirnov (if ks=TRUE) and Cramer-von Mises goodness of fit tests for detection function models.

Usage

```
ds.gof(model, breaks = NULL, nc = NULL, qq = TRUE, ks = FALSE, ...)
```

Arguments

model	fitted model object
breaks	Cutpoints to use for binning data
nc	Number of distance classes
qq	Flag to indicate whether quantile-quantile plot is desired
ks	perform the Kolmogorov-Smirnov test (this involves many bootstraps so can take a while)
...	Graphics parameters to pass into qqplot function

Value

List of test results and a plot.

Author(s)

David L Miller

See Also

qqplot.ddf ddf.gof

Examples

```
## Not run:  
# fit and test a simple model for the golf tee data  
library(Distance)  
data(book.tee.data)  
tee.data<-book.tee.data$book.tee.dataframe[book.tee.data$book.tee.dataframe$observer==1,]  
ds.model <- ds(tee.data,4)  
ds.gof(ds.model)  
  
## End(Not run)
```

ducknest

Ducknest line transect survey data

Description

Simulated line transect survey of duck nests, designed to reproduce the data of Figure 2 in Anderson and Pospahala (1970).

Format

A data frame with 534 rows and 7 variables

Region.Label	strata names (single stratum in this instance)
Area	size of refuge (0 in this case, actual size 60km ²)
Sample.Label	transect ID
Effort	length of transects (km)
object	nest ID
distance	perpendicular distance (m)
Study.Area	name of wildlife refuge

Details

The Monte Vista National Wildlife Refuge is in southern Colorado in the USA at an altitude of roughly 2400m.

Source

Simulated data, from the distance sampling introductory course, Centre for Research into Ecological & Environmental Modelling, University of St Andrews.

References

Anderson, D. R., and R. S. Pospahala. 1970. Correction of bias in belt transect studies of immobile objects. *The Journal of Wildlife Management* 34 (1): 141–146. <https://doi.org/10.2307/3799501>

DuikerCameraTraps *Duiker camera trap survey*

Description

Study took place in Tai National Park Cote d'Ivoire in 2014. Filmed Maxwell's duikers (*Philantomba maxwellii*) were assigned to distance intervals; recorded distances are the midpoints of the intervals. This data includes only observations recorded at times of peak activity.

Format

A data frame with 6277 rows and 6 variables

Region.Label	strata names (single stratum)
Area	size of study area (40.37 km ²)
multiplier	spatial effort, as the proportion of a circle covered by the angle of view of the camera (42 degrees for these c
Sample.Label	camera station identifier (21 functioning cameras in this data set)
Effort	temporal effort, i.e. the number of 2-second time-steps over which the camera operated
distance	radial distance (m) to interval midpoint

Source

Howe, E.J., Buckland, S.T., Després-Einspenner, M.-L. and Kühl, H.S. (2017), Distance sampling with camera traps. *Methods Ecol Evol*, 8: 1558-1565. doi:10.1111/2041-210X.12790

Howe, Eric J. et al. (2018), Data from: Distance sampling with camera traps, Dryad, Dataset, <https://doi.org/10.5061/dryad.b4c70>

ETP_Dolphin

*Eastern Tropical Pacific spotted dolphin survey***Description**

Observers aboard tuna vessels detecting dolphin schools along with a number of possibly useful covariates for modelling the detection function.

Format

A data frame with 1090 rows and 13 variables.

Region.Label	stratum labels (only one)
Area	size (nmi) of each stratum
Sample.Label	transect labels
Effort	transect length (nmi)
object	object ID
distance	perpendicular distance (nmi)
LnCluster	natural log of cluster size
Month	month of detection
Beauf.class	Beaufort sea state
Cue.type	initial cue triggering detection
Search.method	observer method making the detection
size	cluster size
Study.Area	study area name

Note

Several different search methods included in these data

- 0 binoculars from crows nest
- 2 binoculars from elsewhere on ship
- 3 helicopter searching ahead of ship
- 5 radar detects of seabirds above dolphin schools

Source

Inter-American Tropical Tuna Commission

See Also

Several cue types were also recorded by observers.

- 1 seabirds above the school
- 2 water splashes
- 3 unspecified
- 4 floating objects such as logs

flatfile

The flatfile data format

Description

Distance allows loading data as a "flat file" and analyse data (and obtain abundance estimates) straight away, provided that the format of the flat file is correct. One can provide the file as, for example, an Excel spreadsheet using `read.xls` in **gdata** or CSV using `read.csv`.

Details

Each row of the data table corresponds to one observation and must have a the following columns:

distance	observed distance to object
Sample.Label	Identifier for the sample (transect id)
Effort	effort for this transect (e.g. line transect length or number of times point transect was visited)
Region.Label	label for a given stratum (see below)
Area	area of the strata

Note that in the simplest case (one area surveyed only once) there is only one `Region.Label` and a single corresponding `Area` duplicated for each observation.

The example given below was provided by Eric Rexstad.

Examples

```
## Not run:
library(Distance)
# Need to have the gdata library installed from CRAN, requires a system
# with perl installed (usually fine for Linux/Mac)
library(gdata)

# Need to get the file path first
# Going to the path given in the below, one can examine the format
minke.filepath <- system.file("minke.xlsx",package="Distance")

# Load the Excel file, note that header=FALSE and we add column names after
minke <- read.xls(minke.filepath, stringsAsFactor=FALSE,header=FALSE)
```

```

names(minke) <- c("Region.Label", "Area", "Sample.Label", "Effort","distance")
# One may want to call edit(minke) or head(minke) at this point
# to examine the data format

# Due to the way the file was saved and the default behaviour in R
# for numbers stored with many decimal places (they are read as strings
# rather than numbers, see str(minke)). We must coerce the Effort column
# to numeric
minke$Effort <- as.numeric(minke$Effort)

## perform an analysis using the exact distances
pooled.exact <- ds(minke, truncation=1.5, key="hr", order=0)
summary(pooled.exact)

## Try a binned analysis
# first define the bins
dist.bins <- c(0, .214, .428, .643, .857, 1.071, 1.286, 1.5)
pooled.binned <- ds(minke, truncation=1.5, cutpoints=dist.bins, key="hr", order=0)

# binned with stratum as a covariate
minke$stratum <- ifelse(minke$Region.Label=="North", "N", "S")
strat.covar.binned <- ds(minke, truncation=1.5, key="hr",
                        formula=~as.factor(stratum), cutpoints=dist.bins)

# Stratified by North/South
full.strat.binned.North <- ds(minke[minke$Region.Label=="North",],
                             truncation=1.5, key="hr", order=0, cutpoints=dist.bins)
full.strat.binned.South <- ds(minke[minke$Region.Label=="South",],
                              truncation=1.5, key="hr", order=0, cutpoints=dist.bins)

## model summaries
model.sel.bin <- data.frame(name=c("Pooled f(0)", "Stratum covariate",
                                "Full stratification"),
                           aic=c(pooled.binned$ddf$criterion,
                                strat.covar.binned$ddf$criterion,
                                full.strat.binned.North$ddf$criterion+
                                full.strat.binned.South$ddf$criterion))

# Note model with stratum as covariate is most parsimonious
print(model.sel.bin)

## End(Not run)

```

Description

Formal goodness of fit testing for detection function models using Kolmogorov-Smirnov and Cramer-von Mises tests. Both tests are based on looking at the quantile-quantile plot produced by [qqplot.ddf](#)

and deviations from the line $x=y$.

Usage

```
gof_ds(model, plot = TRUE, chisq = FALSE, nboot = 100, ks = FALSE, ...)
```

Arguments

model	a fitted detection function.
plot	if TRUE the Q-Q plot is plotted
chisq	if TRUE then chi-squared statistic is calculated even for models that use exact distances. Ignored for models that use binned distances
nboot	number of replicates to use to calculate p-values for the Kolmogorov-Smirnov goodness of fit test statistics
ks	perform the Kolmogorov-Smirnov test (this involves many bootstraps so can take a while)
...	other arguments to be passed to ddf.gof

Details

The Kolmogorov-Smirnov test asks the question "what's the largest vertical distance between a point and the $y=x$ line?" It uses this distance as a statistic to test the null hypothesis that the samples (EDF and CDF in our case) are from the same distribution (and hence our model fits well). If the deviation between the $y=x$ line and the points is too large we reject the null hypothesis and say the model doesn't have a good fit.

Rather than looking at the single biggest difference between the $y=x$ line and the points in the Q-Q plot, we might prefer to think about all the differences between line and points, since there may be many smaller differences that we want to take into account rather than looking for one large deviation. Its null hypothesis is the same, but the statistic it uses is the sum of the deviations from each of the point to the line.

Details

Note that a bootstrap procedure is required for the Kolmogorov-Smirnov test to ensure that the p-values from the procedure are correct as we are comparing the cumulative distribution function (CDF) and empirical distribution function (EDF) and we have estimated the parameters of the detection function. The nboot parameter controls the number of bootstraps to use. Set to 0 to avoid computing bootstraps (much faster but with no Kolmogorov-Smirnov results, of course).

Examples

```
## Not run:
# fit and test a simple model for the golf tee data
library(Distance)
data(book.tee.data)
tee.data<-book.tee.data$book.tee.dataframe[book.tee.data$book.tee.dataframe$observer==1,]
ds.model <- ds(tee.data,4)
# don't make plot
```

```
gof_ds(ds.model, plot=FALSE)

## End(Not run)
```

golftees

Golf tee data

Description

The data are from independent surveys by eight observers of a population of 250 groups (760 individuals) of golf tees. The tees, of two colours, were placed in groups of between 1 and 8 in a survey region of 1680 m², either exposed above the surrounding grass, or at least partially hidden by it. They were surveyed by the 1999 statistics honours class at the Univ of St Andrews.

Format

The format is:

List of 4 \$ book.tee.dataframe:'data.frame':

\$ object object ID

\$ observer observer ID

\$ detected detected or not detected

\$ distance perpendicular distance

\$ size group size

\$ sex number of tees in group

\$ exposure tee height above ground \$ book.tee.region : 'data.frame': 2 obs. of 2 variables: ..

\$ Region.Label stratum name

\$ Area stratum size \$ book.tee.samples : 'data.frame': 11 obs. of 3 variables: ..

\$ Sample.Label transect label

\$ Region.Label stratum name

\$ Effort transect length \$ book.tee.obs : 'data.frame': 162 obs. of 3 variables:

\$ object object ID

\$ Region.Label stratum in which it was detected

\$ Sample.Label transect on which it was detected

Details

We treat each group of golf tees as a single animal with size equal to the number of tees in the group; yellow tees are male, green are female; tees exposed above the surrounding grass are classified as exposed, others as unexposed. We are grateful to Miguel Bernal for making these data available; they were collected by him as part of a masters project.

References

- Borchers, D. L., S.T. Buckland, and W. Zucchini. 2002. Estimating Animal Abundance: Closed Populations. Statistics for Biology and Health. London: Springer-Verlag. <https://www.springer.com/gp/book/978185233560>
- Buckland, S.T., D.R. Anderson, K.P. Burnham, J.L. Laake, D.L. Borchers, and L. Thomas. Advanced Distance Sampling: Estimating Abundance of Biological Populations. OUP Oxford, 2004.

logLik.dsmode1	<i>log-likelihood value for a fitted detection function</i>
----------------	---

Description

Extract the log-likelihood from a fitted detection function.

Usage

```
## S3 method for class 'dsmode1'
logLik(object, ...)
```

Arguments

object	a fitted detection function model object
...	included for S3 completeness, but ignored

Value

a numeric value giving the log-likelihood with two attributes: "df" the "degrees of freedom" for the model (number of parameters) and "nobs" the number of observations used to fit the model

Author(s)

David L Miller

Examples

```
## Not run:
library(Distance)
data(minke)
model <- ds(minke, truncation=4)
# extract the log likelihood
logLik(model)

## End(Not run)
```

 LTExercise

Simulated line transect survey data

Description

Simulated line transect survey. Twelve transects, detection function is half-normal. True object density is 79.8 animals per km².

Format

A data frame with 106 rows and 7 variables

Region.Label	strata names (single stratum)
Area	size of study area (1 in this case, making abundance and density equal)
Sample.Label	transect ID
Effort	length of transects (km)
object	object ID
distance	perpendicular distance (m)
Study.Area	name of study area

Note

There is no unit object associated with this dataset

Source

Simulated data, from the distance sampling introductory course, Centre for Research into Ecological & Environmental Modelling, University of St Andrews.

 minke

Simulated minke whale data

Description

Data simulated from models fitted to 1992/1993 Southern Hemisphere minke whale data collected by the International Whaling Commission. See Branch and Butterworth (2001) for survey details (survey design is shown in figure 1(e)). Data simulated by David Borchers.

Format

data.frame with 99 observations of 5 variables:

Region.Label	stratum label ("North" or "South")
Area	stratum area
Sample.Label	transect identifier
Effort	transect length
distance	observed distance

Details

Data are included here as both R data and as an Excel spreadsheet to illustrate the "flat file" input method. See [flatfile](#) for how to load this data and an example analysis.

Source

Shipped with the Distance for Windows.

References

Branch, T.A. and D.S. Butterworth (2001) Southern Hemisphere minke whales: standardised abundance estimates from the 1978/79 to 1997/98 IDCR-SOWER surveys. *Journal of Cetacean Research and Management* 3(2): 143-174

Hedley, S.L., and S.T. Buckland. Spatial Models for Line Transect Sampling. *Journal of Agricultural, Biological, and Environmental Statistics* 9, no. 2 (2004): 181-199. doi:10.1198/1085711043578.

Examples

```
data(minke)
head(minke)
```

plot.dsmodel	<i>Plot a fitted detection function</i>
--------------	---

Description

This is just a simple wrapper around [plot.ds](#). See the manual page for that function for more information.

Usage

```
## S3 method for class 'dsmodel'
plot(x, pl.den = 0, ...)
```

Arguments

x	an object of class dsmodel.
pl.den	shading density for histogram (default 0, no shading)
...	extra arguments to be passed to plot.ds .

Value

NULL, just produces a plot.

Author(s)

David L. Miller

See Also

add_df_covar_line

predict.dsmodel *Predictions from a fitted detection function*

Description

Predict detection probabilities (or effective strip widths/effective areas of detection) from a fitted distance sampling model using either the original data (i.e. "fitted" values) or using new data.

Usage

```
## S3 method for class 'dsmodel'
predict(
  object,
  newdata = NULL,
  compute = FALSE,
  esw = FALSE,
  se.fit = FALSE,
  ...
)
```

Arguments

object	ds model object.
newdata	new data. frame for prediction, this must include a column called "distance".
compute	if TRUE compute values and don't use the fitted values stored in the model object.
esw	if TRUE, returns effective strip half-width (or effective area of detection for point transect models) integral from 0 to the truncation distance (width) of $p(y)dy$; otherwise it returns the integral from 0 to truncation width of $p(y)\pi(y)$ where $\pi(y) = 1/w$ for lines and $\pi(y) = 2r/w^2$ for points.
se.fit	should standard errors on the predicted probabilities of detection (or ESW if esw=TRUE) estimated? Stored in the se.fit element
...	for S3 consistency

Details

For line transects, the effective strip half-width (esw=TRUE) is the integral of the fitted detection function over either 0 to W or the specified int.range. The predicted detection probability is the average probability which is simply the integral divided by the distance range. For point transect models, esw=TRUE calculates the effective area of detection (commonly referred to as "nu", this is the integral of $2/\text{width}^2 * r * g(r)$).

Fitted detection probabilities are stored in the model object and these are returned unless compute=TRUE or newdata is specified. compute=TRUE is used to estimate numerical derivatives for use in delta method approximations to the variance.

Note that the ordering of the returned results when no new data is supplied (the "fitted" values) will not necessarily be the same as the data supplied to `ddf`, the data (and hence results from `predict`) will be sorted by object ID (object).

Value

a list with a single element: `fitted`, a vector of average detection probabilities or `esw` values for each observation in the original data `ornewdata`. If `se.fit=TRUE` there is an additional element `$se.fit`, which contains the standard errors of the probabilities of detection or `ESW`.

Author(s)

David L Miller

print.dht_result	<i>Print abundance estimates</i>
------------------	----------------------------------

Description

Print abundance estimates

Usage

```
## S3 method for class 'dht_result'
print(x, report = "abundance", groups = FALSE, ...)
```

Arguments

<code>x</code>	object of class <code>dht_result</code>
<code>report</code>	should "abundance", "density" or "both" be reported?
<code>groups</code>	should abundance/density of groups be produced?
<code>...</code>	unused

print.dsmodel	<i>Simple pretty printer for distance sampling analyses</i>
---------------	---

Description

Simply prints out a brief description of the model which was fitted. For more detailed information use [summary](#).

Usage

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

Arguments

x a distance sampling analysis (result from calling `ds`).
... not passed through, just for S3 compatibility.

Author(s)

David L. Miller

`print.summary.dsmodel` *Print summary of distance detection function model object*

Description

Provides a brief summary of a distance sampling analysis. Including: detection function parameters, model selection criterion, and optionally abundance in the covered (sampled) region and its standard error.

Usage

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

Arguments

x a summary of distance sampling analysis
... unspecified and unused arguments for S3 consistency

Value

Nothing, just prints the summary.

Author(s)

David L. Miller and Jeff Laake

See Also

[summary.ds](#)

 PTEExercise

Simulated point transect survey data

Description

Simulated point transect survey. Thirty point transects, detection function is half-normal. True object density is 79.6 animals per hectare.

Format

A data frame with 144 rows and 7 variables

Region.Label	strata names (single stratum)
Area	size of study area (0 in this case)
Sample.Label	transect ID
Effort	number of visits to point
object	object ID
distance	radial distance (m)
Study.Area	name of study area

Source

Simulated data, from the distance sampling introductory course, Centre for Research into Ecological & Environmental Modelling, University of St Andrews.

 p_dist_table

Distribution of probabilities of detection

Description

Generate a table of frequencies of probability of detection from a detection function model. This is particularly useful when employing covariates, as it can indicate if there are detections with very small detection probabilities that can be unduly influential when calculating abundance estimates.

Arguments

object	fitted detection function
bins	how the results should be binned
proportion	should proportions be returned as well as counts?

Details

Because `dht` uses a Horvitz-Thompson-like estimator, abundance estimates can be sensitive to errors in the estimated probabilities. The estimator is based on $\sum 1/\hat{P}_a(z_i)$, which means that the sensitivity is greater for smaller detection probabilities. As a rough guide, we recommend that the method be not used if more than say 5% of the $\hat{P}_a(z_i)$ are less than 0.2, or if any are less than 0.1. If these conditions are violated, the truncation distance `w` can be reduced. This causes some loss of precision relative to standard distance sampling without covariates.

Value

a `data.frame` with probability bins, counts and (optionally) proportions. The object has an attribute `p_range` which contains the range of estimated detection probabilities

Note

This function is located in the `mrds` package but the documentation is provided here for easy access.

Author(s)

David L Miller

References

Marques, F.F.C. and S.T. Buckland. 2004. Covariate models for the detection function. In: Advanced Distance Sampling, eds. S.T. Buckland, D.R. Anderson, K.P. Burnham, J.L. Laake, D.L. Borchers, and L. Thomas. Oxford University Press.

Examples

```
## Not run:
# example using a model for the minke data
data(minke)
# fit a model
result <- ds(minke, formula=~Region.Label)
# print table
p_dist_table(result)
# with proportions
p_dist_table(result, proportion=TRUE)

## End(Not run)
```

safe_factorize

Safely make the right things factors in data.frames

Description

If you have a formula with `as.factor(var)` in it, this function will create a new column with the factor version of `var` with a column called `as.factor(var)`. Uses `model.frame`

Usage

```
safe_factorize(formula, data)
```

Arguments

```
formula      an R formula
data         a data.frame
```

Value

data, with (maybe) some extra columns

Author(s)

David L Miller

Savannah_sparrow_1980 *Savanna sparrow point transects*

Description

Point transect data collected in Colorado 1980/81 to examine effect of agricultural practices upon avian community.

Format

data.frame with 468 observations of 7 variables:

Region.Label	stratum label (pasture ID)
Area	stratum area (set to 1 so density is reported)
Sample.Label	transect identifier
Effort	number of visits
object	object ID
distance	radial distance (m)
Study.Area	name of study area

Details

Design consisted of point transects placed in multiple pastures (3 in 1980, 4 in 1981). While many species were observed, only data for Savannah sparrows (*Passerculus sandwichensis*) are included here.

Note

Data structure for 1981 data set is identical, but there are 448 observations across 4 pastures.

References

Knopf, F.L., J.A. Sedgwick, and R.W. Cannon. (1988) Guild structure of a riparian avifauna relative to seasonal cattle grazing. *The Journal of Wildlife Management* 52 (2): 280–290. <https://doi.org/10.2307/3801235>.

sikadeer *Sika deer pellet data from southern Scotland*

Description

Because sika deer spend most of their time in woodland areas, abundance estimates are based on pellet group counts. Line transect methods were applied to estimate deer pellet group density by geographic block.

Format

A data frame with 1923 rows and 11 variables.

Region.Label	stratum labels
Area	size (ha) of each stratum
Sample.Label	transect labels
Defecation.rate	rate of dung production per individual per day
Defecation.rate.SE	variability in defecation rate
Decay.rate	time (days) for dung to become undetectable
Decay.rate.SE	variability in decay rate
Effort	transect length (km)
object	object ID
distance	perpendicular distance (cm)
Study.Area	study area name

Details

Data presented here are from the Peebleshire portion of the study described by Marques et al. (2001).

References

Marques, F.F.C., S.T. Buckland, D. Goffin, C.E. Dixon, D.L. Borchers, B.A. Mayle, and A.J. Peace. (2001). Estimating deer abundance from line transect surveys of dung: sika deer in southern Scotland. *Journal of Applied Ecology* 38 (2): 349–363. <https://doi.org/10.1046/j.1365-2664.2001.00584.x>

Stratify_example *Simulated minke whale data*

Description

Data simulated from models fitted to 1992/1993 Southern Hemisphere minke whale data collected by the International Whaling Commission. See Branch and Butterworth (2001) for survey details (survey design is shown in figure 1(e)). Data simulated by David Borchers.

Format

data.frame with 99 observations of 7 variables:

Region.Label	stratum label ("North" or "South")
Area	stratum area (square nautical mile)
Sample.Label	transect identifier
Effort	transect length (nautical mile)
object	object ID
distance	observed distance (nautical mile)
Study.Area	name of study area

References

Branch, T.A. and D.S. Butterworth. (2001) Southern Hemisphere minke whales: standardised abundance estimates from the 1978/79 to 1997/98 IDCR-SOWER surveys. *Journal of Cetacean Research and Management* 3(2): 143-174

Hedley, S.L., and S.T. Buckland. (2004) Spatial models for line transect sampling. *Journal of Agricultural, Biological, and Environmental Statistics* 9: 181-199. doi:10.1198/1085711043578.

summarize_ds_models *Make a table of summary statistics for detection function models*

Description

Provide a summary table of useful information about fitted detection functions. This can be useful when paired with `knitr::kable` function. By default models are sorted by AIC and will therefore not allow models with different truncations and distance binning.

Usage

```
summarize_ds_models(..., sort = "AIC", output = "latex", delta_only = TRUE)
```

Arguments

...	models to be summarised
sort	column to sort by (default "AIC")
output	should the output be given in "latex" compatible format or as "plain" text?
delta_only	only output AIC differences (default TRUE)

Details

Note that the column names are in LaTeX format, so if you plan to manipulate the resulting `data.frame` in R, you may wish to rename the columns for ease of access.

Author(s)

David L Miller

Examples

```
## Not run:
# fit some models to the golf tee data
library(Distance)
data(book.tee.data)
tee.data<-book.tee.data$book.tee.dataframe[book.tee.data$book.tee.dataframe$observer==1,]
model_hn <- ds(tee.data,4)
model_hr <- ds(tee.data,4, key="hr")
summarize_ds_models(model_hr, model_hn, output="plain")

## End(Not run)
```

summary.dht_bootstrap *Summarize bootstrap abundance uncertainty estimate output*

Description

A simple function to calculate summaries of bootstrap output generated by [bootdht](#).

Usage

```
## S3 method for class 'dht_bootstrap'
summary(object, alpha = 0.05, ...)
```

Arguments

<code>object</code>	output from <code>bootdht</code>
<code>alpha</code>	value to use in confidence interval calculation (to obtain $\alpha/2$ and $1-\alpha/2$ intervals)
<code>...</code>	for S3 compatibility, unused.

Details

Summaries are only made for numeric outputs. Both median and mean are reported to allow assessment of bias. The coefficient of variation reported (in column `cv`) is based on the median calculated from the bootstraps.

Value

a `data.frame` of summary statistics

summary.dsmodel *Summary of distance sampling analysis*

Description

Provides a brief summary of a distance sampling analysis. This includes

Usage

```
## S3 method for class 'dsmodel'
summary(object, ...)
```

Arguments

object a distance analysis
 ... unspecified and unused arguments for S3 consistency

Value

list of extracted and summarized objects

Note

This function just calls [summary.ds](#) and [dht](#), collates and prints the results in a nice way.

Author(s)

David L. Miller

Systematic_variance_1 *Simulation of encounter rate variance*

Description

Simulated line transect data with large differences in transect length. In `systematic_var_2` that transect length gradient is coupled with a strong animal gradient; exaggerating encounter rate variance between transects.

Format

data.frame with 253 observations of 7 variables:

Region.Label	stratum label (default)
Area	stratum area (0.5 km ²)
Sample.Label	transect identifier
Effort	transect length (km)
object	object ID
distance	perpendicular distance (m)
Study.Area	name of study area

Details

True population size is 1000 objects in the study area of size 0.5 km²; such that true density is 2000 objects per km.

Note

Data structure for `systematic_var_2` is identical, but there are 256 observations and a strong animal gradient.

References

Fewster, R.M., S.T. Buckland, K.P. Burnham, D.L. Borchers, P.E. Jupp, J.L. Laake and L. Thomas. (2009) Estimating the encounter rate variance in distance sampling. *Biometrics* 65 (1): 225–236. <https://doi.org/10.1111/j.1541-0420.2008.01018.x>.

`unflatten`*Unflatten flatfile data.frames*

Description

Sometimes data is provided in the `flatfile` format, but we really want it in `mrds` format (that is, as distance data, observation table, sample table and region table format). This function undoes the flattening, assuming that the data have the correct columns.

Usage

```
unflatten(data)
```

Arguments

`data` data in flatfile format (a `data.frame`)

Value

list of four `data.frames`: distance data, observation table, sample table, region table.

Author(s)

David L Miller

unimak *Simulated line transect survey data with covariates*

Description

Simulated line transect survey. Only eight line transects, detection function is half-normal.

Format

A data frame with 60 rows and 9 variables

Region.Label	strata names (single stratum)
Area	size of study area (mi ²)
Sample.Label	transect ID
Effort	transect length (mi)
object	object ID
distance	perpendicular distance (km)
MSTD0	time since medication taken by observer (min)
Hour	time of day of sighting (hour)
Study.Area	name of study area

Note

Hour is covariate that has no effect on detection function, while MSTD0 does affect the detection function. Examine the ability of model selection to choose the correct model.

Source

Simulated data, from the distance sampling introductory course, Centre for Research into Ecological & Environmental Modelling, University of St Andrews.

units_table *Generate table of unit conversions*

Description

Returns a table of conversions between the units used in Distance for Windows. This is extracted from the DistIni.mdb default database.

Usage

```
units_table()
```

Author(s)

David L Miller

wren

*Steve Buckland's winter wren surveys***Description**

Observations of winter wren (*Troglodytes troglodytes* L.) collected by Steve Buckland in woodland/parkland at Montrave Estate near Leven, Fife, Scotland.

Details

Four different surveys were carried out:

wren_5min 5-minute point count

wren_snapshot snapshot method

wren_cuecount cue count

wren_lt line transect survey

Note

wren_5min is data frame with 134 observations of 8 variables

Region.Label	stratum name (single stratum)
Area	size (ha) of Montrave study area
Sample.Label	point label
Effort	Number of visits to point
object	Object ID
distance	radial distance (m)
direction	direction of detection from point
Study.Area	Montrave Estate

wren_snapshot is data frame with 119 observations of 7 variables

Region.Label	stratum name (single stratum)
Area	size (ha) of Montrave study area
Sample.Label	point label
Effort	Number of visits to point
object	Object ID
distance	radial distance (m)
Study.Area	Montrave Estate

wren_cuecount is data frame with 774 observations of 9 variables

Region.Label	stratum name (single stratum)
Area	size (ha) of Montrave study area

Sample.Label	point label
Cue.rate	Production rate (per min) of cues
Cue.rate.SE	SE of cue production rate
object	Object ID
distance	radial distance (m)
Search.time	Time (min) listening for cues
Study.Area	Montrave Estate

wren_It is data frame with 156 observations of 8 variables

Region.Label	stratum name (single stratum)
Area	size (ha) of Montrave study area
Sample.Label	transect label
Effort	transect length (km)
object	Object ID
distance	perpendicular distance (m)
Study.Area	Montrave Estate

Source

Steve Buckland

References

Buckland, S. T. (2006) Point-transect surveys for songbirds: robust methodologies. *The Auk* 123 (2): 345–357.

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