

Package ‘unmarked’

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Type Package

Title Models for Data from Unmarked Animals

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Rcpp (>= 0.8.0)

Description Fits hierarchical models of animal abundance and occurrence to data collected using survey methods such as point counts, site occupancy sampling, distance sampling, removal sampling, and double observer sampling. Parameters governing the state and observation processes can be modeled as functions of covariates.

License GPL (>= 3)

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Collate 'classes.R' 'unmarkedEstimate.R' 'mapInfo.R' 'unmarkedFrame.R'
'unmarkedFit.R' 'utils.R' 'getDesign.R' 'colect.R' 'distsamp.R'
'multinomPois.R' 'occu.R' 'occuRN.R' 'occuMulti.R' 'pcount.R'
'gmultmix.R' 'pcountOpen.R' 'gdistsamp.R' 'unmarkedFitList.R'
'unmarkedLinComb.R' 'ranef.R' 'boot.R' 'occuFP.R' 'gpcount.R'
'occuPEN.R' 'pcount.spHDS.R' 'occuMS.R' 'occuTTD.R'
'distsampOpen.R' 'multmixOpen.R' 'unmarkedCrossVal.R' 'piFun.R'
'vif.R' 'makePiFun.R' 'posteriorSamples.R'

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<https://sites.google.com/site/unmarkedinfo/home>,
<http://github.com/ianfiske/unmarked>,
<http://github.com/rbchan/unmarked>

BugReports <https://github.com/rbchan/unmarked/issues>

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R topics documented:

unmarked-package	4
backTransform-methods	8
birds	9
coef-methods	9
colext	10
computeMPLElambda	13
confint-methods	14
crossbill	15
crossVal	17
cruz	19
csvToUMF	20
detFuns	21
distsamp	22
distsampOpen	26
fitList	30
fitted-methods	31
formatDistData	32
formatMult	34
formatWideLong	35
frogs	36
gdistsamp	37
getB-methods	40
getFP-methods	40
getP-methods	40
gf	41
gmultmix	41
gpcount	44
imputeMissing	46

issj	47
jay	48
lambda2psi	50
linearComb-methods	51
linetran	51
makePiFuns	52
mallard	54
masspcru	55
modSel	56
multinomPois	57
multmixOpen	59
nonparboot-methods	63
occu	65
occuFP	67
occuMS	69
occuMulti	78
occuPEN	82
occuPEN_CV	85
occuRN	87
occuTTD	89
ovendata	93
parboot	94
pcount	96
pcount.spHDS	98
pcountOpen	100
piFuns	104
pointtran	106
posteriorSamples	107
predict-methods	108
ranef-methods	109
SE-methods	111
sight2perpdist	112
simulate-methods	112
SSE	113
Switzerland	114
unmarkedEstimate-class	115
unmarkedEstimateList-class	116
unmarkedFit-class	116
unmarkedFitList-class	119
unmarkedFrame	120
unmarkedFrame-class	122
unmarkedFrameDS	124
unmarkedFrameDSO	126
unmarkedFrameMMO	128
unmarkedFrameMPois	130
unmarkedFrameOccu	132
unmarkedFrameOccuFP	134
unmarkedFrameOccuMS	135

unmarkedFrameOccuMulti	137
unmarkedFrameOccuTTD	138
unmarkedFramePCO	140
unmarkedFramePCount	142
unmarkedMultFrame	144
unmarkedRanef-class	147
vcov-methods	148
vif	148
[-methods	149

Index	151
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unmarked-package	<i>Models for Data from Unmarked Animals</i>
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Description

Fits hierarchical models of animal occurrence and abundance to data collected on species that may be detected imperfectly. Models include single- and multi-season site occupancy models, binomial N-mixture models, and multinomial N-mixture models. The data can arise from survey methods such as occurrence sampling, temporally replicated counts, removal sampling, double observer sampling, and distance sampling. Parameters governing the state and observation processes can be modeled as functions of covariates. General treatment of these models can be found in MacKenzie et al. (2006) and Royle and Dorazio (2008). The primary reference for the package is Fiske and Chandler (2011).

Details

Overview of Model-fitting Functions:

[occu](#) fits occurrence models with no linkage between abundance and detection (MacKenzie et al. 2002).

[occuRN](#) fits abundance models to presence/absence data by exploiting the link between detection probability and abundance (Royle and Nichols 2003).

[occuFP](#) fits occupancy models to data characterized by false negatives and false positive detections (e.g., Royle and Link [2006] and Miller et al. [2011]).

[occuMulti](#) fits multi-species occupancy model of Rota et al. [2016].

[colext](#) fits the mutli-season occupancy model of MacKenzie et al. (2003).

[pcount](#) fits N-mixture models (aka binomial mixture models) to repeated count data (Royle 2004a, Kery et al 2005).

[distsamp](#) fits the distance sampling model of Royle et al. (2004) to distance data recorded in discrete intervals.

[gdistsamp](#) fits the generalized distance sampling model described by Chandler et al. (2011) to distance data recorded in discrete intervals.

[gpcount](#) fits the generalized N-mixture model described by Chandler et al. (2011) to repeated count data collected using the robust design.

`multinomPois` fits the multinomial-Poisson model of Royle (2004b) to data collected using methods such as removal sampling or double observer sampling.

`gmultmix` fits a generalized form of the multinomial-mixture model of Royle (2004b) that allows for estimating availability and detection probability.

`pcountOpen` fits the open population model of Dail and Madsen (2011) to repeated count data. This is a generalized form of the Royle (2004a) N-mixture model that includes parameters for recruitment and apparent survival.

Data: All data are passed to unmarked's estimation functions as a formal S4 class called an `unmarkedFrame`, which has child classes for each model type. This allows metadata (eg as distance interval cut points, measurement units, etc...) to be stored with the response and covariate data. See `unmarkedFrame` for a detailed description of `unmarkedFrames` and how to create them.

Model Specification: `unmarked`'s model-fitting functions allow specification of covariates for both the state process and the detection process. For two-level hierarchical models, (eg `occu`, `occuRN`, `pcount`, `multinomPois`, `distsamp`) covariates for the detection process (at the site or observation level) and the state process (at the site level) are specified with a double right-hand sided formula, in that order. Such a formula looks like

$$x_1 + x_2 + \dots + x_n \quad x_1 + x_2 + \dots + x_n$$

where x_1 through x_n are additive covariates of the process of interest. Using two tildes in a single formula differs from standard R convention, but it is informative about the model being fit. The meaning of these covariates, or what they model, is full described in the help files for the individual functions and is not the same for all functions. For models with more than two processes (eg `coltext`, `gmultmix`, `pcountOpen`), single right-hand sided formulas (only one tilde) are used to model each parameter.

Utility Functions: `unmarked` contains several utility functions for organizing data into the form required by its model-fitting functions. `csvToUMF` converts an appropriately formatted comma-separated values (.csv) file to a list containing the components required by model-fitting functions.

Author(s)

Ian Fiske, Richard Chandler, Andy Royle, Marc Kéry, David Miller, and Rebecca Hutchinson

References

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Examples

```
## An example site-occupancy analysis

# Simulate occupancy data
set.seed(344)
nSites <- 100
nReps <- 5
covariates <- data.frame(veght=rnorm(nSites),
  habitat=factor(c(rep('A', 50), rep('B', 50))))

psipars <- c(-1, 1, -1)
ppars <- c(1, -1, 0)
X <- model.matrix(~veght+habitat, covariates) # design matrix
psi <- plogis(X %*% psipars)
p <- plogis(X %*% ppars)

y <- matrix(NA, nSites, nReps)
```

```

z <- rbinom(nSites, 1, psi)      # true occupancy state
for(i in 1:nSites) {
  y[i,] <- rbinom(nReps, 1, z[i]*p[i])
}

# Organize data and look at it
umf <- unmarkedFrameOccu(y = y, siteCovs = covariates)
head(umf)
summary(umf)

# Fit some models
fm1 <- occu(~1 ~1, umf)
fm2 <- occu(~veght+habitat ~veght+habitat, umf)
fm3 <- occu(~veght ~veght+habitat, umf)

# Model selection
fms <- fitList(m1=fm1, m2=fm2, m3=fm3)
modSel(fms)

# Empirical Bayes estimates of the number of sites occupied
sum(bup(ranef(fm3), stat="mode"))    # Sum of posterior modes
sum(z)                               # Actual

# Model-averaged prediction and plots

# psi in each habitat type
newdata1 <- data.frame(habitat=c('A', 'B'), veght=0)
Epsi1 <- predict(fms, type="state", newdata=newdata1)
with(Epsi1, {
  plot(1:2, Predicted, xaxt="n", xlim=c(0.5, 2.5), ylim=c(0, 0.5),
       xlab="Habitat",
       ylab=expression(paste("Probability of occurrence (", psi, ")")),
       cex.lab=1.2,
       pch=16, cex=1.5)
  axis(1, 1:2, c('A', 'B'))
  arrows(1:2, Predicted-SE, 1:2, Predicted+SE, angle=90, code=3, length=0.05)
})

# psi and p as functions of vegetation height
newdata2 <- data.frame(habitat=factor('A', levels=c('A','B')),
  veght=seq(-2, 2, length=50))
Epsi2 <- predict(fms, type="state", newdata=newdata2, appendData=TRUE)
Ep <- predict(fms, type="det", newdata=newdata2, appendData=TRUE)

op <- par(mfrow=c(2, 1), mai=c(0.9, 0.8, 0.2, 0.2))
plot(Predicted~veght, Epsi2, type="l", lwd=2, ylim=c(0,1),
     xlab="Vegetation height (standardized)",
     ylab=expression(paste("Probability of occurrence (", psi, ")")))
lines(lower ~ veght, Epsi2, col=gray(0.7))

```

```

    lines(upper ~ veght, Epsi2, col=gray(0.7))
plot(Predicted~veght, Ep, type="l", lwd=2, ylim=c(0,1),
     xlab="Vegetation height (standardized)",
     ylab=expression(paste("Detection probability (", italic(p), ")")))
lines(lower~veght, Ep, col=gray(0.7))
lines(upper~veght, Ep, col=gray(0.7))
par(op)

```

backTransform-methods *Methods for Function backTransform in Package 'unmarked'*

Description

Methods for function backTransform in Package 'unmarked'. This converts from link-scale to original-scale

Usage

```

## S4 method for signature 'unmarkedFit'
backTransform(obj, type)
## S4 method for signature 'unmarkedEstimate'
backTransform(obj)

```

Arguments

obj	Object of appropriate S4 class
type	one of names(obj), eg 'state' or 'det'

Methods

obj = "unmarkedEstimate" Typically done internally

obj = "unmarkedFit" Back-transform a parameter from a fitted model. Only possible if no co-variates are present. Must specify argument type as one of the values returned by names(obj).

obj = "unmarkedLinComb" Back-transform a predicted value created by linearComb. This is done internally by [predict](#) but can be done explicitly by user.

Examples

```

data(mallard)
mallardUMF <- unmarkedFramePCount(mallard.y, siteCovs = mallard.site,
  obsCovs = mallard.obs)

(fm <- pcount(~ 1 ~ forest, mallardUMF)) # Fit a model
backTransform(fm, type="det") # This works because there are no detection covariates
#backTransform(fm, type="state") # This doesn't work because covariates are present
lc <- linearComb(fm, c(1, 0), type="state") # Estimate abundance on the log scale when forest=0
backTransform(lc) # Abundance on the original scale

```


birds

*BBS Point Count and Occurrence Data from 2 Bird Species***Description**

Data frames for 2 species from the breeding bird survey (BBS). Each data frame has a row for each site and columns for each sampling event. There is a point count and occurrence—designated by .bin— version for each species.

Usage

```
data(birds)
```

Format

catbird A data frame of point count observations for the catbird.

catbird.bin A data frame of occurrence observations for the catbird.

woodthrush A data frame of point count observations for the wood thrush.

woodthrush.bin A data frame of point count observations for the wood thrush.

Source

Royle J. N-mixture models for estimating population size from spatially replicated counts. *Biometrics*. 2004. 60(1):108–115.

Examples

```
data(birds)
```

coef-methods

*Methods for Function coef in Package 'unmarked'***Description**

Extract coefficients

Usage

```
## S4 method for signature 'unmarkedFit'
coef(object, type, altNames = TRUE)
## S4 method for signature 'unmarkedEstimate'
coef(object, altNames = TRUE, ...)
## S4 method for signature 'linCombOrBackTrans'
coef(object)
```

Arguments

<code>object</code>	Object of appropriate S4 class
<code>type</code>	Either 'state' or 'det'
<code>altNames</code>	Return specific names for parameter estimates?
<code>...</code>	Further arguments. Not currently used

Value

A named numeric vector of parameter estimates.

Methods

`object = "linCombOrBackTrans"` Object from `linearComb`
`object = "unmarkedEstimate"` `unmarkedEstimate` object
`object = "unmarkedFit"` Fitted model

colext

Fit the dynamic occupancy model of MacKenzie et. al (2003)

Description

Estimate parameters of the colonization-extinction model, including covariate-dependent rates and detection process.

Usage

```
colext(psiformula= ~1, gammaformula = ~ 1, epsilonformula = ~ 1,
      pformula = ~ 1, data, starts, method="BFGS", se=TRUE, ...)
```

Arguments

<code>psiformula</code>	Right-hand sided formula for the initial probability of occupancy at each site.
<code>gammaformula</code>	Right-hand sided formula for colonization probability.
<code>epsilonformula</code>	Right-hand sided formula for extinction probability.
<code>pformula</code>	Right-hand sided formula for detection probability.
<code>data</code>	<code>unmarkedMultFrame</code> object that supplies the data (see unmarkedMultFrame).
<code>starts</code>	optionally, initial values for parameters in the optimization.
<code>method</code>	Optimization method used by optim .
<code>se</code>	logical specifying whether or not to compute standard errors.
<code>...</code>	Additional arguments to <code>optim</code> , such as lower and upper bounds

Details

This function fits the colonization-extinction model of MacKenzie et al (2003). The colonization and extinction rates can be modeled with covariates that vary yearly at each site using a logit link. These covariates are supplied by special `unmarkedMultFrame` `yearlySiteCovs` slot. These parameters are specified using the `gammaformula` and `epsilonformula` arguments. The initial probability of occupancy is modeled by covariates specified in the `psiformula`.

The conditional detection rate can also be modeled as a function of covariates that vary at the secondary sampling period (ie., repeat visits). These covariates are specified by the first part of the `formula` argument and the data is supplied via the usual `obsCovs` slot.

The projected and smoothed trajectories (Weir et al 2009) can be obtained from the `smoothed.mean` and `projected.mean` slots (see examples).

Value

`unmarkedFitColExt` object describing model fit.

References

MacKenzie, D.I. et al. (2002) Estimating Site Occupancy Rates When Detection Probabilities Are Less Than One. *Ecology*, 83(8), 2248-2255.

MacKenzie, D. I., J. D. Nichols, J. E. Hines, M. G. Knutson, and A. B. Franklin. 2003. Estimating site occupancy, colonization, and local extinction when a species is detected imperfectly. *Ecology* 84:2200–2207.

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Weir L. A., Fiske I. J., Royle J. (2009) Trends in Anuran Occupancy from Northeastern States of the North American Amphibian Monitoring Program. *Herpetological Conservation and Biology*. 4(3):389-402.

See Also

[nonparboot](#), [unmarkedMultFrame](#), and [formatMult](#)

Examples

```
# Fake data
R <- 4 # number of sites
J <- 3 # number of secondary sampling occasions
T <- 2 # number of primary periods

y <- matrix(c(
  1,1,0, 0,0,0,
  0,0,0, 0,0,0,
  1,1,1, 1,1,0,
  1,0,1, 0,0,1), nrow=R, ncol=J*T, byrow=TRUE)
y

site.covs <- data.frame(x1=1:4, x2=factor(c('A','B','A','B')))
```

```

site.covs

yearly.site.covs <- list(
  year = matrix(c(
    'year1', 'year2',
    'year1', 'year2',
    'year1', 'year2',
    'year1', 'year2'), nrow=R, ncol=T, byrow=TRUE)
)
yearly.site.covs

obs.covs <- list(
  x4 = matrix(c(
    -1,0,1, -1,1,1,
    -2,0,0, 0,0,2,
    -3,1,0, 1,1,2,
    0,0,0, 0,1,-1), nrow=R, ncol=J*T, byrow=TRUE),
  x5 = matrix(c(
    'a','b','c', 'a','b','c',
    'd','b','a', 'd','b','a',
    'a','a','c', 'd','b','a',
    'a','b','a', 'd','b','a'), nrow=R, ncol=J*T, byrow=TRUE))
obs.covs

umf <- unmarkedMultFrame(y=y, siteCovs=site.covs,
  yearlySiteCovs=yearly.site.covs, obsCovs=obs.covs,
  numPrimary=2) # organize data
umf # look at data
summary(umf) # summarize
fm <- colext(~1, ~1, ~1, ~1, umf) # fit a model
fm

## Not run:
# Real data
data(frogs)
umf <- formatMult(masspcru)
obsCovs(umf) <- scale(obsCovs(umf))

## Use 1/4 of data just for run speed in example
umf <- umf[which((1:numSites(umf)) %% 4 == 0),]

## constant transition rates
(fm <- colext(psiformula = ~ 1,
  gammaformula = ~ 1,
  epsilonformula = ~ 1,
  pformula = ~ JulianDate + I(JulianDate^2), umf, control = list(trace=1, maxit=1e4)))

## get the trajectory estimates
smoothed(fm)
projected(fm)

```

```

# Empirical Bayes estimates of number of sites occupied in each year
re <- ranef(fm)
modes <- colSums(bup(re, stat="mode"))
plot(1:7, modes, xlab="Year", ylab="Sites occupied", ylim=c(0, 70))

## Find bootstrap standard errors for smoothed trajectory
fm <- nonparboot(fm, B = 100) # This takes a while!
fm@smoothed.mean.bsse

## try yearly transition rates
yearlySiteCovs(umf) <- data.frame(year = factor(rep(1:7, numSites(umf))))
(fm.yearly <- colext(psiformula = ~ 1,
  gammaformula = ~ year,
  epsilonformula = ~ year,
  pformula = ~ JulianDate + I(JulianDate^2), umf,
  control = list(trace=1, maxit=1e4)))

## End(Not run)

```

computeMPLElambda	<i>Compute the penalty weight for the MPLE penalized likelihood method</i>
-------------------	--

Description

This function computes the weight for the MPLE penalty of Moreno & Lele (2010).

Usage

```
computeMPLElambda(formula, data, knownOcc=numeric(0), starts,
  method="BFGS", engine=c("C", "R"))
```

Arguments

formula	Double right-hand side formula describing covariates of detection and occupancy in that order.
data	An unmarkedFrameOccu object
knownOcc	Vector of sites that are known to be occupied. These should be supplied as row numbers of the y matrix, eg, c(3,8) if sites 3 and 8 were known to be occupied a priori.
starts	Vector of parameter starting values.
method	Optimization method used by optim .
engine	Either "C" or "R" to use fast C++ code or native R code during the optimization.

Details

See [occuPEN](#) for details and examples.

Value

The computed lambda.

Author(s)

Rebecca A. Hutchinson

References

Moreno, M. and S. R. Lele. 2010. Improved estimation of site occupancy using penalized likelihood. *Ecology* 91: 341-346.

See Also

[unmarked](#), [unmarkedFrameOccu](#), [occu](#), [occuPEN](#), [occuPEN_CV](#), [nonparboot](#)

confint-methods

Methods for Function confint in Package ‘unmarked’

Description

Methods for function confint in Package ‘unmarked’

Usage

```
## S4 method for signature 'unmarkedBackTrans'
confint(object, parm, level)
## S4 method for signature 'unmarkedEstimate'
confint(object, parm, level)
## S4 method for signature 'unmarkedLinComb'
confint(object, parm, level)
## S4 method for signature 'unmarkedFit'
confint(object, parm, level, type, method)
```

Arguments

object	Object of appropriate S4 class
parm	Name of parameter(s) of interest
level	Level of confidence
type	Either "state" or "det"
method	Either "normal" or "profile"

Value

A vector of lower and upper confidence intervals. These are asymptotic unless method='profile' is used on unmarkedFit objects in which case they are profile likelihood intervals.

See Also[unmarkedFit-class](#)

crossbill	<i>Detection/non-detection data on the European crossbill (Loxia curvirostra)</i>
-----------	---

Description

267 1-kmsq quadrats were surveyed 3 times per year during 1999-2007.

Usage

```
data(crossbill)
```

Format

A data frame with 267 observations on the following 58 variables.

id Plot ID

ele Elevation

forest Percent forest cover

surveys a numeric vector

det991 Detection data for 1999, survey 1

det992 Detection data for 1999, survey 2

det993 Detection data for 1999, survey 3

det001 Detection data for 2000, survey 1

det002 a numeric vector

det003 a numeric vector

det011 a numeric vector

det012 a numeric vector

det013 a numeric vector

det021 a numeric vector

det022 a numeric vector

det023 a numeric vector

det031 a numeric vector

det032 a numeric vector

det033 a numeric vector

det041 a numeric vector

det042 a numeric vector

det043 a numeric vector

det051 a numeric vector
det052 a numeric vector
det053 a numeric vector
det061 a numeric vector
det062 a numeric vector
det063 Detection data for 2006, survey 3
det071 Detection data for 2007, survey 1
det072 Detection data for 2007, survey 2
det073 Detection data for 2007, survey 3
date991 Day of the season for 1999, survey 1
date992 Day of the season for 1999, survey 2
date993 Day of the season for 1999, survey 3
date001 Day of the season for 2000, survey 1
date002 a numeric vector
date003 a numeric vector
date011 a numeric vector
date012 a numeric vector
date013 a numeric vector
date021 a numeric vector
date022 a numeric vector
date023 a numeric vector
date031 a numeric vector
date032 a numeric vector
date033 a numeric vector
date041 a numeric vector
date042 a numeric vector
date043 a numeric vector
date051 a numeric vector
date052 a numeric vector
date053 a numeric vector
date061 a numeric vector
date062 a numeric vector
date063 a numeric vector
date071 a numeric vector
date072 a numeric vector
date073 Day of the season for 2007, survey 3

Source

Schmid, H. N. Zbinden, and V. Keller. 2004. Überwachung der Bestandsentwicklung häufiger Brutvogel in der Schweiz, Swiss Ornithological Institute Sempach Switzerland

See Also

[Switzerland](#) for corresponding covariate data defined for all 1-kmsq pixels in Switzerland. Useful for making species distribution maps.

Examples

```
data(crossbill)
str(crossbill)
```

crossVal

Cross-validation methods for fitted unmarked models and fit lists

Description

Test predictive accuracy of fitted models using several cross-validation approaches. The dataset is divided by site only into folds or testing and training datasets (i.e., encounter histories within sites are never split up).

Usage

```
## S4 method for signature 'unmarkedFit'
crossVal(
  object, method=c("Kfold","holdout","leaveOneOut"),
  folds=10, holdoutPct=0.25, statistic=RMSE_MAE, parallel=FALSE, ...)
## S4 method for signature 'unmarkedFitList'
crossVal(
  object, method=c("Kfold","holdout","leaveOneOut"),
  folds=10, holdoutPct=0.25, statistic=RMSE_MAE, parallel=FALSE,
  sort = c("none", "increasing", "decreasing"), ...)
```

Arguments

object	A fitted model inheriting class <code>unmarkedFit</code> or a list of fitted models with class <code>unmarkedFitList</code>
method	Cross validation method to use as string. Valid options are "Kfold", "holdout", or "leaveOneOut"
folds	Number of folds to use for k-fold cross validation
holdoutPct	Proportion of dataset (value between 0-1) to use as the "holdout" or "test" set, for the holdout method

statistic	Function that calculates statistics for each fold. The function must take an <code>unmarkedFit</code> object as the first argument and return a named numeric vector with statistic value(s). The default function <code>RMSE_MAE</code> returns root-mean-square error and mean absolute error. See <code>unmarked::RMSE_MAE</code> for an example of correct statistic function structure.
parallel	If <code>TRUE</code> , run folds in parallel. This may speed up cross-validation if the unmarked model takes a long time to fit or you have a large number of sites and are using leave-one-out cross-validation.
sort	If doing cross-validation on a <code>fitList</code> , you can optionally sort the resulting table(s) of statistic values for each model.
...	Other arguments passed to the statistic function.

Value

`unmarkedCrossVal` or `unmarkedCrossValList` object containing calculated statistic values for each fold.

Author(s)

Ken Kellner <contact@kenkellner.com>

See Also

[fitList](#), [unmarkedFit](#)

Examples

```
## Not run:
#Get data
data(frogs)
pferUMF <- unmarkedFrameOccu(pfer.bin)
siteCovs(pferUMF) <- data.frame(sitevar1 = rnorm(numSites(pferUMF)))
obsCovs(pferUMF) <- data.frame(obsvar1 = rnorm(numSites(pferUMF) * obsNum(pferUMF)))

#Fit occupancy model
fm <- occu(~ obsvar1 ~ 1, pferUMF)

#k-fold cross validation with 10 folds
(kfold = crossVal(fm, method="Kfold", folds=10))

#holdout method with 25
(holdout = crossVal(fm, method='holdout', holdoutPct=0.25))

#Leave-one-out method
(leave = crossVal(fm, method='leaveOneOut'))

#Fit a second model and combine into a fitList
fm2 <- occu(~1 ~1, pferUMF)
fl <- fitList(fm2, fm)
```

```
#Cross-validation for all fits in fitList using holdout method
(cvlist <- crossVal(fl, method='holdout'))
```

```
## End(Not run)
```

cruz

Landscape data for Santa Cruz Island

Description

Spatially-referenced elevation, forest cover, and vegetation data for Santa Cruz Island.

Usage

```
data(cruz)
```

Format

A data frame with 2787 observations on the following 5 variables.

x Easting (meters)

y Northing (meters)

elevation a numeric vector, FEET (multiply by 0.3048 to convert to meters)

forest a numeric vector, proportion cover

chaparral a numeric vector, proportion cover

Details

The resolution is 300x300 meters.

The Coordinate system is EPSG number 26911

NAD_1983_UTM_Zone_11N Projection: Transverse_Mercator False_Easting: 500000.000000 False_Northing: 0.000000 Central_Meridian: -117.000000 Scale_Factor: 0.999600 Latitude_Of_Origin: 0.000000

Linear Unit: Meter GCS_North_American_1983 Datum: D_North_American_1983

Source

Brian Cohen of the Nature Conservancy helped prepare the data

References

Sillett, S. and Chandler, R.B. and Royle, J.A. and Kery, M. and Morrison, S.A. In Press. Hierarchical distance sampling models to estimate population size and habitat-specific abundance of an island endemic. *Ecological Applications*

Examples

```

data(cruz)
str(cruz)

levelplot(elevation ~ x + y, cruz, aspect="iso",
  col.regions=terrain.colors(100))

if(require(raster)) {
  elev <- rasterFromXYZ(cruz[,1:3],
    crs="+proj=utm +zone=11 +ellps=GRS80 +datum=NAD83 +units=m +no_defs")
  elev
  plot(elev)
}

```

 csvToUMF

 Convert .CSV File to an unmarkedFrame

Description

This function converts an appropriately formatted comma-separated values file (.csv) to a format usable by *unmarked*'s fitting functions (see *Details*).

Usage

```
csvToUMF(filename, long=FALSE, type, species, ...)
```

Arguments

filename	string describing filename of file to read in
long	FALSE if file is in long format or TRUE if file is in long format (see <i>Details</i>)
species	if data is in long format with multiple species, then this can specify a particular species to extract if there is a column named "species".
type	specific type of unmarkedFrame.
...	further arguments to be passed to the unmarkedFrame constructor.

Details

This function provides a quick way to take a .csv file with headers named as described below and provides the data required and returns of data in the format required by the model-fitting functions in *unmarked*. The .csv file can be in one of 2 formats: long or wide. See the first 2 lines of the *examples* for what these formats look like.

The .csv file is formatted as follows:

- col 1 is site labels.

- if data is in long format, col 2 is date of observation.
- next J columns are the observations (y) - counts or 0/1's.
- next is a series of columns for the site variables (one column per variable). The column header is the variable name.
- next is a series of columns for the observation-level variables. These are in sets of J columns for each variable, e.g., var1-1 var1-2 var1-3 var2-1 var2-2 var2-3, etc. The column header of the first variable in each group must indicate the variable name.

Value

an unmarkedFrame object

Author(s)

Ian Fiske <ianfiske@gmail.com>

Examples

```
# examine a correctly formatted long .csv
head(read.csv(system.file("csv", "frog2001pcru.csv", package="unmarked"))))

# examine a correctly formatted wide .csv
head(read.csv(system.file("csv", "widewt.csv", package="unmarked"))))

# convert them!
dat1 <- csvToUMF(system.file("csv", "frog2001pcru.csv", package="unmarked"),
                  long = TRUE, type = "unmarkedFrameOccu")
dat2 <- csvToUMF(system.file("csv", "frog2001pfer.csv", package="unmarked"),
                  long = TRUE, type = "unmarkedFrameOccu")
dat3 <- csvToUMF(system.file("csv", "widewt.csv", package="unmarked"),
                  long = FALSE, type = "unmarkedFrameOccu")
```

detFuns

Distance-sampling detection functions and associated density functions

Description

These functions represent the currently available detection functions used for modeling line and point transect data with [distsamp](#). Detection functions begin with "g", and density functions begin with a "d".

Usage

```
gxhn(x, sigma)
gxexp(x, rate)
gxhaz(x, shape, scale)
```

```

dxhn(x, sigma)
dxexp(x, rate)
dxhaz(x, shape, scale)
drhn(r, sigma)
drex(r, rate)
drhaz(r, shape, scale)

```

Arguments

x	Perpendicular distance
r	Radial distance
sigma	Shape parameter of half-normal detection function
rate	Shape parameter of negative-exponential detection function
shape	Shape parameter of hazard-rate detection function
scale	Scale parameter of hazard-rate detection function

See Also

[distsamp](#) for example of using these for plotting detection function

Examples

```

# Detection probabilities at 25m for range of half-normal sigma values.
round(gxhn(25, 10:15), 2)

# Plot negative exponential distributions
plot(function(x) gxexp(x, rate=10), 0, 50, xlab="distance",
      ylab="Detection probability")
plot(function(x) gxexp(x, rate=20), 0, 50, add=TRUE, lty=2)
plot(function(x) gxexp(x, rate=30), 0, 50, add=TRUE, lty=3)

# Plot half-normal probability density functions for line- and point-transects
par(mfrow=c(2, 1))
plot(function(x) dxhn(x, 20), 0, 50, xlab="distance",
      ylab="Probability density", main="Line-transect")
plot(function(x) drhn(x, 20), 0, 50, xlab="distance",
      ylab="Probability density", main="Point-transect")

```

distsamp

Fit the hierarchical distance sampling model of Royle et al. (2004)

Description

Fit the hierarchical distance sampling model of Royle et al. (2004) to line or point transect data recorded in discrete distance intervals.

Usage

```
distsamp(formula, data, keyfun=c("halfnorm", "exp",
  "hazard", "uniform"), output=c("density", "abund"),
  unitsOut=c("ha", "kmsq"), starts, method="BFGS", se=TRUE,
  engine=c("C", "R"), rel.tol=0.001, ...)
```

Arguments

formula	Double right-hand formula describing detection covariates followed by abundance covariates. ~1 ~1 would be a null model.
data	object of class unmarkedFrameDS, containing response matrix, covariates, distance interval cut points, survey type ("line" or "point"), transect lengths (for survey = "line"), and units ("m" or "km") for cut points and transect lengths. See example for set up.
keyfun	One of the following detection functions: "halfnorm", "hazard", "exp", or "uniform." See details.
output	Model either "density" or "abund"
unitsOut	Units of density. Either "ha" or "kmsq" for hectares and square kilometers, respectively.
starts	Vector of starting values for parameters.
method	Optimization method used by optim .
se	logical specifying whether or not to compute standard errors.
engine	Use code written in C++ or R
rel.tol	Requested relative accuracy of the integral, see integrate
...	Additional arguments to optim, such as lower and upper bounds

Details

Unlike conventional distance sampling, which uses the 'conditional on detection' likelihood formulation, this model is based upon the unconditional likelihood and allows for modeling both abundance and detection function parameters.

The latent transect-level abundance distribution $f(N|\theta)$ assumed to be Poisson with mean λ (but see [gdistsamp](#) for alternatives).

The detection process is modeled as multinomial: $y_{ij} \sim Multinomial(N_i, \pi_{ij})$, where π_{ij} is the multinomial cell probability for transect i in distance class j . These are computed based upon a detection function $g(x|\sigma)$, such as the half-normal, negative exponential, or hazard rate.

Parameters λ and σ can be vectors affected by transect-specific covariates using the log link.

Value

unmarkedFitDS object (child class of [unmarkedFit-class](#)) describing the model fit.

Note

You cannot use obsCovs.

Author(s)

Richard Chandler <rbchan@uga.edu>

References

Royle, J. A., D. K. Dawson, and S. Bates (2004) Modeling abundance effects in distance sampling. *Ecology* 85, pp. 1591-1597.

Sillett, S. and Chandler, R.B. and Royle, J.A. and Kery, M. and Morrison, S.A. In Press. Hierarchical distance sampling models to estimate population size and habitat-specific abundance of an island endemic. *Ecological Applications*

See Also

[unmarkedFrameDS](#), [unmarkedFit-class fitList](#), [formatDistData](#), [parboot](#), [sight2perpdist](#), [detFuns](#), [gdistsamp](#), [ranef](#). Also look at [vignette\("distsamp"\)](#).

Examples

```
## Line transect examples

data(linetran)

ltUMF <- with(linetran, {
  unmarkedFrameDS(y = cbind(dc1, dc2, dc3, dc4),
    siteCovs = data.frame(Length, area, habitat),
    dist.breaks = c(0, 5, 10, 15, 20),
    tlength = linetran$Length * 1000, survey = "line", unitsIn = "m")
})

ltUMF
summary(ltUMF)
hist(ltUMF)

# Half-normal detection function. Density output (log scale). No covariates.
(fm1 <- distsamp(~ 1 ~ 1, ltUMF))

# Some methods to use on fitted model
summary(fm1)
backTransform(fm1, type="state")          # animals / ha
exp(coef(fm1, type="state", altNames=TRUE)) # same
backTransform(fm1, type="det")             # half-normal SD
hist(fm1, xlab="Distance (m)") # Only works when there are no det covars
# Empirical Bayes estimates of posterior distribution for N_i
plot(ranef(fm1, K=50))

# Effective strip half-width
(eshw <- integrate(gxhn, 0, 20, sigma=10.9)$value)

# Detection probability
eshw / 20 # 20 is strip-width
```



```

# Halfnormal. Covariates affecting both density and detection.
(fm2 <- distsamp(~area + habitat ~ habitat, ltUMF))

# Hazard-rate detection function.
(fm3 <- distsamp(~ 1 ~ 1, ltUMF, keyfun="hazard"))

# Plot detection function.
fmhz.shape <- exp(coef(fm3, type="det"))
fmhz.scale <- exp(coef(fm3, type="scale"))
plot(function(x) gxxhaz(x, shape=fmhz.shape, scale=fmhz.scale), 0, 25,
xlab="Distance (m)", ylab="Detection probability")

## Point transect examples

# Analysis of the Island Scrub-jay data.
# See Sillett et al. (In press)

data(issj)
str(issj)

jayumf <- unmarkedFrameDS(y=as.matrix(issj[,1:3]),
  siteCovs=data.frame(scale(issj[,c("elevation", "forest", "chaparral")])),
  dist.breaks=c(0,100,200,300), unitsIn="m", survey="point")

(fm1jay <- distsamp(~chaparral ~chaparral, jayumf))

## Not run:

data(pointtran)

ptUMF <- with(pointtran, {
  unmarkedFrameDS(y = cbind(dc1, dc2, dc3, dc4, dc5),
  siteCovs = data.frame(area, habitat),
  dist.breaks = seq(0, 25, by=5), survey = "point", unitsIn = "m")
})

# Half-normal.
(fmp1 <- distsamp(~ 1 ~ 1, ptUMF))
hist(fmp1, ylim=c(0, 0.07), xlab="Distance (m)")

# effective radius
sig <- exp(coef(fmp1, type="det"))
ea <- 2*pi * integrate(grhn, 0, 25, sigma=sig)$value # effective area
sqrt(ea / pi) # effective radius

# detection probability
ea / (pi*25^2)

```

```
## End(Not run)
```

distsampOpen

Open population model for distance sampling data

Description

Fit the model of Dail and Madsen (2011) and Hostetler and Chandler (2015) with a distance sampling observation model (Sollmann et al. 2015).

Usage

```
distsampOpen(lambdaformula, gammaformula, omegaformula, pformula,
  data, keyfun=c("halfnorm", "exp", "hazard", "uniform"),
  output=c("abund", "density"), unitsOut=c("ha", "kmsq"),
  mixture=c("P", "NB", "ZIP"), K,
  dynamics=c("constant", "autoreg", "notrend", "trend", "ricker", "gompertz"),
  fix=c("none", "gamma", "omega"), immigration=FALSE, iotaformula = ~1,
  starts, method="BFGS", se=TRUE, ...)
```

Arguments

lambdaformula	Right-hand sided formula for initial abundance
gammaformula	Right-hand sided formula for recruitment rate (when dynamics is "constant", "autoreg", or "notrend") or population growth rate (when dynamics is "trend", "ricker", or "gompertz")
omegaformula	Right-hand sided formula for apparent survival probability (when dynamics is "constant", "autoreg", or "notrend") or equilibrium abundance (when dynamics is "ricker" or "gompertz")
pformula	A right-hand side formula describing the detection function covariates
data	An object of class unmarkedFramedSO
keyfun	One of the following detection functions: "halfnorm", "hazard", "exp", or "uniform"
output	Model either "density" or "abund"
unitsOut	Units of density. Either "ha" or "kmsq" for hectares and square kilometers, respectively
mixture	String specifying mixture: "P", "NB", or "ZIP" for the Poisson, negative binomial, or zero-inflated Poisson distributions respectively
K	Integer defining upper bound of discrete integration. This should be higher than the maximum observed count and high enough that it does not affect the parameter estimates. However, the higher the value the slower the computation

dynamics	Character string describing the type of population dynamics. "constant" indicates that there is no relationship between omega and gamma. "autoreg" is an auto-regressive model in which recruitment is modeled as $\gamma N[i,t-1]$. "notrend" model gamma as $\lambda(1-\omega)$ such that there is no temporal trend. "trend" is a model for exponential growth, $N[i,t] = N[i,t-1]\gamma$, where gamma in this case is finite rate of increase (normally referred to as lambda). "ricker" and "gompertz" are models for density-dependent population growth. "ricker" is the Ricker-logistic model, $N[i,t] = N[i,t-1]\exp(\gamma(1 - N[i,t-1]/\omega))$, where gamma is the maximum instantaneous population growth rate (normally referred to as r) and omega is the equilibrium abundance (normally referred to as K). "gompertz" is a modified version of the Gompertz-logistic model, $N[i,t] = N[i,t-1]\exp(\gamma(1 - \log(N[i,t-1]+1)/\log(\omega+1)))$, where the interpretations of gamma and omega are similar to in the Ricker model
fix	If "omega", omega is fixed at 1. If "gamma", gamma is fixed at 0
immigration	Logical specifying whether or not to include an immigration term (iota) in population dynamics
iotaformula	Right-hand sided formula for average number of immigrants to a site per time step
starts	Vector of starting values
method	Optimization method used by optim
se	Logical specifying whether or not to compute standard errors
...	Additional arguments to optim, such as lower and upper bounds

Details

These models generalize distance sampling models (Buckland et al. 2001) by relaxing the closure assumption (Dail and Madsen 2011, Hostetler and Chandler 2015, Sollmann et al. 2015).

The models include two or three additional parameters: gamma, either the recruitment rate (births and immigrations), the finite rate of increase, or the maximum instantaneous rate of increase; omega, either the apparent survival rate (deaths and emigrations) or the equilibrium abundance (carrying capacity); and iota, the number of immigrants per site and year. Estimates of population size at each time period can be derived from these parameters, and thus so can trend estimates. Or, trend can be estimated directly using `dynamics="trend"`.

When immigration is set to FALSE (the default), iota is not modeled. When immigration is set to TRUE and dynamics is set to "autoreg", the model will separately estimate birth rate (gamma) and number of immigrants (iota). When immigration is set to TRUE and dynamics is set to "trend", "ricker", or "gompertz", the model will separately estimate local contributions to population growth (gamma and omega) and number of immigrants (iota).

The latent abundance distribution, $f(N|\theta)$ can be set as a Poisson, negative binomial, or zero-inflated Poisson random variable, depending on the setting of the mixture argument, `mixture = "P"`, `mixture = "NB"`, `mixture = "ZIP"` respectively. For the first two distributions, the mean of N_i is λ_i . If $N_i \sim NB$, then an additional parameter, α , describes dispersion (lower α implies higher variance). For the ZIP distribution, the mean is $\lambda_i(1 - \psi)$, where psi is the zero-inflation parameter.

For "constant", "autoreg", or "notrend" dynamics, the latent abundance state following the initial sampling period arises from a Markovian process in which survivors are modeled as $S_{it} \sim$

$Binomial(N_{it-1}, \omega_{it})$, and recruits follow $G_{it} \sim Poisson(\gamma_{it})$. Alternative population dynamics can be specified using the dynamics and immigration arguments.

λ_i , γ_{it} , and ι_{it} are modeled using the log link. p_{ijt} is modeled using the logit link. ω_{it} is either modeled using the logit link (for "constant", "autoreg", or "notrend" dynamics) or the log link (for "ricker" or "gompertz" dynamics). For "trend" dynamics, ω_{it} is not modeled.

For the distance sampling detection process, half-normal ("halfnorm"), exponential ("exp"), hazard ("hazard"), and uniform ("uniform") key functions are available.

Value

An object of class `unmarkedFitDSO`

Warning

This function can be extremely slow, especially if there are covariates of gamma or omega. Consider testing the timing on a small subset of the data, perhaps with `se=FALSE`. Finding the lowest value of K that does not affect estimates will also help with speed.

Note

When gamma or omega are modeled using year-specific covariates, the covariate data for the final year will be ignored; however, they must be supplied.

If the time gap between primary periods is not constant, an M by T matrix of integers should be supplied to `unmarkedFrameDSO` using the `primaryPeriod` argument.

Secondary sampling periods are optional, but can greatly improve the precision of the estimates.

Optimization may fail if the initial value of the intercept for the detection parameter (sigma) is too small or large relative to transect width. By default, this parameter is initialized at $\log(\text{average band width})$. You may have to adjust this starting value.

Author(s)

Richard Chandler, Jeff Hostetler, Andy Royle, Ken Kellner

References

- Buckland, S.T., Anderson, D.R., Burnham, K.P., Laake, J.L., Borchers, D.L. and Thomas, L. (2001) *Introduction to Distance Sampling: Estimating Abundance of Biological Populations*. Oxford University Press, Oxford, UK.
- Dail, D. and L. Madsen (2011) Models for Estimating Abundance from Repeated Counts of an Open Metapopulation. *Biometrics*. 67: 577-587.
- Hostetler, J. A. and R. B. Chandler (2015) Improved State-space Models for Inference about Spatial and Temporal Variation in Abundance from Count Data. *Ecology* 96: 1713-1723.
- Sollmann, R., Gardner, B., Chandler, R.B., Royle, J.A. and Sillett, T.S. (2015) An open-population hierarchical distance sampling model. *Ecology* 96: 325-331.

See Also

`distsamp`, `gdistsamp`, `unmarkedFrameDSO`

Examples

```
## Not run:

#Generate some data
set.seed(123)
lambda=4; gamma=0.5; omega=0.8; sigma=25;
M=100; T=10; J=4
y <- array(NA, c(M, J, T))
N <- matrix(NA, M, T)
S <- G <- matrix(NA, M, T-1)
db <- c(0, 25, 50, 75, 100)

#Half-normal, line transect
g <- function(x, sig) exp(-x^2/(2*sig^2))

cp <- u <- a <- numeric(J)
L <- 1
a[1] <- L*db[2]
cp[1] <- integrate(g, db[1], db[2], sig=sigma)$value
for(j in 2:J) {
  a[j] <- db[j+1] - sum(a[1:j])
  cp[j] <- integrate(g, db[j], db[j+1], sig=sigma)$value
}
u <- a / sum(a)
cp <- cp / a * u
cp[j+1] <- 1-sum(cp)

for(i in 1:M) {
  N[i,1] <- rpois(1, lambda)
  y[i,1:J,1] <- rmultinom(1, N[i,1], cp)[1:J]

  for(t in 1:(T-1)) {
    S[i,t] <- rbinom(1, N[i,t], omega)
    G[i,t] <- rpois(1, gamma)
    N[i,t+1] <- S[i,t] + G[i,t]
    y[i,1:J,t+1] <- rmultinom(1, N[i,t+1], cp)[1:J]
  }
}
y <- matrix(y, M)

#Make a covariate
sc <- data.frame(x1 = rnorm(M))

umf <- unmarkedFrameDSO(y = y, siteCovs=sc, numPrimary=T, dist.breaks=db,
  survey="line", unitsIn="m", tlength=rep(1, M))

(fit <- distsampOpen(~x1, ~1, ~1, ~1, data = umf, K=50, keyfun="halfnorm"))

#Compare to truth
cf <- coef(fit)
data.frame(model=c(exp(cf[1]), cf[2], exp(cf[3]), plogis(cf[4]), exp(cf[5])),
```

```

      truth=c(lambda, 0, gamma, omega, sigma))

#Predict
head(predict(fit, type='lambda'))

#Check fit with parametric bootstrap
pb <- parboot(fit, nsims=15)
plot(pb)

# Empirical Bayes estimates of abundance for each site / year
re <- ranef(fit)
plot(re, layout=c(10,5), xlim=c(-1, 10))

## End(Not run)

```

fitList	<i>constructor of unmarkedFitList objects</i>
---------	---

Description

Organize models for model selection or model-averaged prediction.

Usage

```
fitList(..., fits)
```

Arguments

...	Fitted models. Preferably named.
fits	An alternative way of providing the models. A (preferably named) list of fitted models.

Note

Two requirements exist to conduct AIC-based model-selection and model-averaging in unmarked. First, the data objects (ie, unmarkedFrames) must be identical among fitted models. Second, the response matrix must be identical among fitted models after missing values have been removed. This means that if a response value was removed in one model due to missingness, it needs to be removed from all models.

Author(s)

Richard Chandler <rbchan@uga.edu>

Examples

```

data(linetran)
(dbreaksLine <- c(0, 5, 10, 15, 20))
lengths <- linetran$Length * 1000

ltUMF <- with(linetran, {
  unmarkedFrameDS(y = cbind(dc1, dc2, dc3, dc4),
    siteCovs = data.frame(Length, area, habitat), dist.breaks = dbreaksLine,
    tlength = lengths, survey = "line", unitsIn = "m")
})

fm1 <- distsamp(~ 1 ~1, ltUMF)
fm2 <- distsamp(~ area ~1, ltUMF)
fm3 <- distsamp(~ 1 ~area, ltUMF)

## Two methods of creating an unmarkedFitList using fitList()

# Method 1
fmList <- fitList(Null=fm1, .area=fm2, area.=fm3)

# Method 2. Note that the argument name "fits" must be included in call.
models <- list(Null=fm1, .area=fm2, area.=fm3)
fmList <- fitList(fits = models)

# Extract coefficients and standard errors
coef(fmList)
SE(fmList)

# Model-averaged prediction
predict(fmList, type="state")

# Model selection
modSel(fmList, nullmod="Null")

```

fitted-methods

Methods for Function fitted in Package 'unmarked'

Description

Extracted fitted values from a fitted model.

Usage

```

## S4 method for signature 'unmarkedFit'
fitted(object, na.rm = FALSE)
## S4 method for signature 'unmarkedFitColExt'
fitted(object, na.rm = FALSE)
## S4 method for signature 'unmarkedFitOccu'
fitted(object, na.rm = FALSE)

```

```
## S4 method for signature 'unmarkedFitOccuRN'
fitted(object, K, na.rm = FALSE)
## S4 method for signature 'unmarkedFitPCount'
fitted(object, K, na.rm = FALSE)
## S4 method for signature 'unmarkedFitDS'
fitted(object, na.rm = FALSE)
```

Arguments

object	A fitted model of appropriate S4 class
K	Integer specifying upper bound of integration.
na.rm	Logical. Should missing values be removed from data?

Value

Returns a matrix of expected values

Methods

```
object = "unmarkedFit" A fitted model
object = "unmarkedFitColExt" A model fit by colext
object = "unmarkedFitOccu" A model fit by occu
object = "unmarkedFitOccuRN" A model fit by occuRN
object = "unmarkedFitPCount" A model fit by pcount
object = "unmarkedFitDS" A model fit by distsamp
```

formatDistData	<i>Bin distance data</i>
----------------	--------------------------

Description

Convert individual-level distance data to the transect-level format required by [distsamp](#) or [gdistsamp](#)

Usage

```
formatDistData(distData, distCol, transectNameCol, dist.breaks,
               occasionCol, effortMatrix)
```

Arguments

distData	data.frame where each row is a detected individual. Must have at least 2 columns. One for distances and the other for transect names.
distCol	character, name of the column in distData that contains the distances. The distances should be numeric.

transectNameCol	character, column name containing transect names. The transect column should be a factor.
dist.breaks	numeric vector of distance interval cutpoints. Length must equal J+1.
occasionCol	optional character. If transects were visited more than once, this can be used to format data for <code>gdistsamp</code> . It is the name of the column in <code>distData</code> that contains the occasion numbers. The occasion column should be a factor.
effortMatrix	optional matrix of 1 and 0s that is $M \times J$ in size and will allow for the insertion of NAs where the matrix = 0, indicating that a survey was not completed. When not supplied a matrix of all 1s is created since it is assumed all surveys were completed.

Details

This function creates a site (M) by distance interval (J) response matrix from a `data.frame` containing the detection distances for each individual and the transect names. Alternatively, if each transect was surveyed T times, the resulting matrix is $M \times JT$, which is the format required by `gdistsamp`, see `unmarkedFrameGDS`.

Value

An $M \times J$ or $M \times JT$ matrix containing the binned distance data. Transect names will become rownames and colnames will describe the distance intervals.

Note

It is important that the factor containing transect names includes levels for all the transects surveyed, not just those with ≥ 1 detection. Likewise, if transects were visited more than once, the factor containing the occasion numbers should include levels for all occasions. See the example for how to add levels to a factor.

See Also

`distsamp`, `unmarkedFrame`

Examples

```
# Create a data.frame containing distances of animals detected
# along 4 transects.
dat <- data.frame(transect=gl(4,5, labels=letters[1:4]),
                  distance=rpois(20, 10))

dat

# Look at your transect names.
levels(dat$transect)

# Suppose that you also surveyed a transect named "e" where no animals were
# detected. You must add it to the levels of dat$transect
levels(dat$transect) <- c(levels(dat$transect), "e")
levels(dat$transect)
```

```

# Distance cut points defining distance intervals
cp <- c(0, 8, 10, 12, 14, 18)

# Create formatted response matrix
yDat <- formatDistData(dat, "distance", "transect", cp)
yDat

# Now you could merge yDat with transect-level covariates and
# then use unmarkedFrameDS to prepare data for distsamp

## Example for data from multiple occasions

dat2 <- data.frame(distance=1:100, site=gl(5, 20),
                  visit=factor(rep(1:4, each=5)))
cutpt <- seq(0, 100, by=25)
y2 <- formatDistData(dat2, "distance", "site", cutpt, "visit")
umf <- unmarkedFrameGDS(y=y2, numPrimary=4, survey="point",
                      dist.breaks=cutpt, unitsIn="m")
## Example for data from multiple occasions with effortMatrix

dat3 <- data.frame(distance=1:100, site=gl(5, 20), visit=factor(rep(1:4, each=5)))
cutpt <- seq(0, 100, by=25)

effortMatrix <- matrix(ncol=4, nrow=5, rbinom(20,1,0.8))

y3 <- formatDistData(dat2, "distance", "site", cutpt, "visit", effortMatrix)

```

formatMult

Create unmarkedMultFrame from Long Format Data Frame

Description

This convenience function converts multi-year data in long format to unmarkedMultFrame Object. See Details for more information.

Usage

```
formatMult(df.in)
```

Arguments

`df.in` a data.frame appropriately formatted (see Details).

Details

`df.in` is a data frame with columns formatted as follows:

Column 1 = year number

Column 2 = site name or number

Column 3 = julian date or chronological sample number during year

Column 4 = observations (y)

Column 5 – Final Column = covariates

Note that if the data is already in wide format, it may be easier to create an `unmarkedMultFrame` object directly with a call to `unmarkedMultFrame`.

Value

`unmarkedMultFrame` object

<code>formatWideLong</code>	<i>Convert between wide and long data formats.</i>
-----------------------------	--

Description

Convert a `data.frame` between wide and long formats.

Usage

```
formatWide(dfin, sep = ".", obsToY, type, ...)
formatLong(dfin, species = NULL, type, ...)
```

Arguments

<code>dfin</code>	A <code>data.frame</code> to be reformatted.
<code>sep</code>	A separator of column names in wide format.
<code>obsToY</code>	Optional matrix specifying relationship between covariate column structure and response matrix structure.
<code>type</code>	Type of <code>unmarkedFrame</code> to create?
<code>species</code>	Character name of species response column
<code>...</code>	Further arguments to the <code>unmarkedFrame*</code> constructor functions

Details

Note that not all possible `unmarkedFrame*` classes have been tested with these functions. Multinomial data sets (e.g., removal, double-observer, capture-recapture) are almost certainly easier to enter directly to the constructor function and are not supported by `formatLong` or `formatWide`.

In order for these functions to work, the columns of `dfin` need to be in the correct order. `formatLong` requires that the columns are in the following scheme:

1. site name or number.

- 2. date or observation number.
- 3. response variable (detections, counts, etc).
- 4. The remaining columns are observation-level covariates.

formatWide requires particular names for the columns. The column order for formatWide is

- 1. (optional) site name, named “site”.
- 2. response, named “y.1”, “y.2”, ..., “y.J”.
- 3. columns of site-level covariates, each with a relevant name per column.
- 4. groups of columns of observation-level covariates, each group having the name form “someObsCov.1”, “someObsCov.2”, ..., “someObsCov.J”.

Value

A data.frame

See Also

[csvToUMF](#)

frogs	<i>2001 Delaware North American Amphibian Monitoring Program Data</i>
-------	---

Description

frogs contains NAAMP data for Pseudacris feriarum (pfer) and Pseudacris crucifer (pcru) in 2001.

Usage

data(frogs)

Format

- pcru.y** matrix of observed calling indices for pcru
- pcru.bin** matrix of detections for pcru
- pcru.data** array of covariates measured at the observation-level for pcru
- pfer.y** matrix of observed calling indices for pfer
- pfer.bin** matrix of detections for pfer
- pfer.data** array of covariates measured at the observation-level for pfer

Details

The rows of pcru.y, pcru.bin, pfer.y, and pfer.bin correspond to sites and columns correspond to visits to each site. The first 2 dimensions of pfer.data and pcru.data are matrices of covariates that correspond to the observation matrices (sites \times observation), with the 3rd dimension corresponding to separate covariates.

Source

<https://www.pwrc.usgs.gov/naamp/>

References

Mossman MJ, Weir LA. North American Amphibian Monitoring Program (NAAMP). Amphibian Declines: the conservation status of United States species. University of California Press, Berkeley, California, USA. 2005:307-313.

Examples

```
data(frogs)
str(pcru.data)
```

gdistsamp

Fit the generalized distance sampling model of Chandler et al. (2011).

Description

Extends the distance sampling model of Royle et al. (2004) to estimate the probability of being available for detection. Also allows abundance to be modeled using the negative binomial distribution.

Usage

```
gdistsamp(lambdaformula, phiformula, pformula, data, keyfun =
c("halfnorm", "exp", "hazard", "uniform"), output = c("abund",
"density"), unitsOut = c("ha", "kmsq"), mixture = c("P", "NB"), K,
starts, method = "BFGS", se = TRUE, engine=c("C", "R"), rel.tol=1e-4, ...)
```

Arguments

lambdaformula	A right-hand side formula describing the abundance covariates.
phiformula	A right-hand side formula describing the availability covariates.
pformula	A right-hand side formula describing the detection function covariates.
data	An object of class unmarkedFrameGDS
keyfun	One of the following detection functions: "halfnorm", "hazard", "exp", or "uniform." See details.
output	Model either "density" or "abund"
unitsOut	Units of density. Either "ha" or "kmsq" for hectares and square kilometers, respectively.
mixture	Either "P" or "NB" for the Poisson and negative binomial models of abundance.
K	An integer value specifying the upper bound used in the integration.
starts	A numeric vector of starting values for the model parameters.

method	Optimization method used by optim .
se	logical specifying whether or not to compute standard errors.
engine	Either "C" to use fast C++ code or "R" to use native R code during the optimization.
rel.tol	relative accuracy for the integration of the detection function. See integrate . You might try adjusting this if you get an error message related to the integral. Alternatively, try providing different starting values.
...	Additional arguments to optim, such as lower and upper bounds

Details

This model extends the model of Royle et al. (2004) by estimating the probability of being available for detection ϕ . This effectively relaxes the assumption that $g(0) = 1$. In other words, individuals at a distance of 0 are not assumed to be detected with certainty. To estimate this additional parameter, replicate distance sampling data must be collected at each transect. Thus the data are collected at $i = 1, 2, \dots, R$ transects on $t = 1, 2, \dots, T$ occasions. As with the model of Royle et al. (2004), the detections must be binned into distance classes. These data must be formatted in a matrix with R rows, and JT columns where J is the number of distance classes. See [unmarkedFrameGDS](#) for more information.

Value

An object of class `unmarkedFitGDS`.

Note

If you aren't interested in estimating ϕ , but you want to use the negative binomial distribution, simply set `numPrimary=1` when formatting the data.

Note

You cannot use `obsCovs`, but you can use `yearlySiteCovs` (a confusing name since this model isn't for multi-year data. It's just a hold-over from the `colect` methods of formatting data upon which it is based.)

Author(s)

Richard Chandler <rbchan@uga.edu>

References

- Royle, J. A., D. K. Dawson, and S. Bates. 2004. Modeling abundance effects in distance sampling. *Ecology* 85:1591-1597.
- Chandler, R. B., J. A. Royle, and D. I. King. 2011. Inference about density and temporary emigration in unmarked populations. *Ecology* 92:1429-1435.

See Also

[distsamp](#)

Examples

```

# Simulate some line-transect data

set.seed(36837)

R <- 50 # number of transects
T <- 5 # number of replicates
strip.width <- 50
transect.length <- 100
breaks <- seq(0, 50, by=10)

lambda <- 5 # Abundance
phi <- 0.6 # Availability
sigma <- 30 # Half-normal shape parameter

J <- length(breaks)-1
y <- array(0, c(R, J, T))
for(i in 1:R) {
  M <- rpois(1, lambda) # Individuals within the 1-ha strip
  for(t in 1:T) {
    # Distances from point
    d <- runif(M, 0, strip.width)
    # Detection process
    if(length(d)) {
      cp <- phi*exp(-d^2 / (2 * sigma^2)) # half-normal w/ g(0)<1
      d <- d[rbinom(length(d), 1, cp) == 1]
      y[i,,t] <- table(cut(d, breaks, include.lowest=TRUE))
    }
  }
}
y <- matrix(y, nrow=R) # convert array to matrix

# Organize data
umf <- unmarkedFrameGDS(y = y, survey="line", unitsIn="m",
  dist.breaks=breaks, tlength=rep(transect.length, R), numPrimary=T)
summary(umf)

# Fit the model
m1 <- gdistsamp(~1, ~1, ~1, umf, output="density", K=50)

summary(m1)

backTransform(m1, type="lambda")
backTransform(m1, type="phi")
backTransform(m1, type="det")

## Not run:
# Empirical Bayes estimates of abundance at each site

```

```
re <- ranef(m1)
plot(re, layout=c(10,5), xlim=c(-1, 20))

## End(Not run)
```

getB-methods

Methods for Function getB in Package 'unmarked'

Description

Methods for function getB in Package 'unmarked'. These methods return a matrix of probabilities detections were certain for occupancy models that account for false positives.

getFP-methods

Methods for Function getFP in Package 'unmarked'

Description

Methods for function getFP in Package 'unmarked'. These methods return a matrix of false positive detection probabilities.

getP-methods

Methods for Function getP in Package 'unmarked'

Description

Methods for function getP in Package 'unmarked'. These methods return a matrix of detection probabilities.

Methods

object = "unmarkedFit" A fitted model object
object = "unmarkedFitDS" A fitted model object
object = "unmarkedFitMPois" A fitted model object
object = "unmarkedFitGMM" A fitted model object

gf	<i>Green frog count index data</i>
----	------------------------------------

Description

Multinomial calling index data.

Usage

```
data(gf)
```

Format

A list with 2 components

gf.data 220 x 3 matrix of count indices

gf.obs list of covariates

References

Royle, J. Andrew, and William A. Link. 2005. A General Class of Multinomial Mixture Models for Anuran Calling Survey Data. *Ecology* 86, no. 9: 2505–2512.

Examples

```
data(gf)
str(gf.data)
str(gf.obs)
```

gmultmix	<i>Generalized multinomial N-mixture model</i>
----------	--

Description

A three level hierarchical model for designs involving repeated counts that yield multinomial outcomes. Possible data collection methods include repeated removal sampling and double observer sampling. The three model parameters are abundance, availability, and detection probability.

Usage

```
gmultmix(lambdaformula, phiformula, pformula, data,
mixture = c("P", "NB"), K, starts, method = "BFGS", se = TRUE, engine=c("C", "R"), ...)
```

Arguments

lambdaformula	Righthand side (RHS) formula describing abundance covariates
phiformula	RHS formula describing availability covariates
pformula	RHS formula describing detection covariates
data	An object of class <code>unmarkedFrameGMM</code>
mixture	Either "P" or "NB" for Poisson and Negative Binomial mixing distributions.
K	The upper bound of integration
starts	Starting values
method	Optimization method used by <code>optim</code>
se	Logical. Should standard errors be calculated?
engine	Either "C" to use fast C++ code or "R" to use native R code during the optimization.
...	Additional arguments to <code>optim</code> , such as lower and upper bounds

Details

The latent transect-level super-population abundance distribution $f(M|\theta)$ can be set as either a Poisson or a negative binomial random variable, depending on the setting of the `mixture` argument. `mixture = "P"` or `mixture = "NB"` select the Poisson or negative binomial distribution respectively. The mean of M_i is λ_i . If $M_i \sim NB$, then an additional parameter, α , describes dispersion (lower α implies higher variance).

The number of individuals available for detection at time j is modeled as binomial: $N_{ij} \sim \text{Binomial}(M_i, \phi_{ij})$.

The detection process is modeled as multinomial: $\mathbf{y}_{it} \sim \text{Multinomial}(N_{it}, \pi_{it})$, where π_{ijt} is the multinomial cell probability for plot i at time t on occasion j .

Cell probabilities are computed via a user-defined function related to the sampling design. Alternatively, the default functions `removalPiFun` or `doublePiFun` can be used for equal-interval removal sampling or double observer sampling. Note that the function for computing cell probabilities is specified when setting up the data using `unmarkedFrameGMM`.

Parameters λ , ϕ and p can be modeled as linear functions of covariates using the log, logit and logit links respectively.

Value

An object of class `unmarkedFitGMM`.

Note

In the case where availability for detection is due to random temporary emigration, population density at time j , $D(i,j)$, can be estimated by $N(i,j)/\text{plotArea}$.

This model is also applicable to sampling designs in which the local population size is closed during the J repeated counts, and availability is related to factors such as the probability of vocalizing. In this case, density can be estimated by $M(i)/\text{plotArea}$.

If availability is a function of both temporary emigration and other processes such as song rate, then density cannot be directly estimated, but inference about the super-population size, $M(i)$, is possible.

Three types of covariates can be supplied, site-level, site-by-year-level, and observation-level. These must be formatted correctly when organizing the data with [unmarkedFrameGPC](#)

Author(s)

Richard Chandler <rbchan@uga.edu> and Andy Royle

References

Royle, J. A. (2004) Generalized estimators of avian abundance from count survey data. *Animal Biodiversity and Conservation* 27, pp. 375–386.

Chandler, R. B., J. A. Royle, and D. I. King. 2011. Inference about density and temporary emigration in unmarked populations. *Ecology* 92:1429-1435.

See Also

[unmarkedFrameGMM](#) for setting up the data and metadata. [multinomPois](#) for surveys where no secondary sampling periods were used. Example functions to calculate multinomial cell probabilities are described [piFuns](#)

Examples

```
# Simulate data using the multinomial-Poisson model with a
# repeated constant-interval removal design.

n <- 100 # number of sites
T <- 4   # number of primary periods
J <- 3   # number of secondary periods

lam <- 3
phi <- 0.5
p <- 0.3

#set.seed(26)
y <- array(NA, c(n, T, J))
M <- rpois(n, lam)          # Local population size
N <- matrix(NA, n, T)       # Individuals available for detection

for(i in 1:n) {
  N[i,] <- rbinom(T, M[i], phi)
  y[i,,1] <- rbinom(T, N[i,], p) # Observe some
  Nleft1 <- N[i,] - y[i,,1]      # Remove them
  y[i,,2] <- rbinom(T, Nleft1, p) # ...
  Nleft2 <- Nleft1 - y[i,,2]
  y[i,,3] <- rbinom(T, Nleft2, p)
}
```

```

y.ijst <- cbind(y[,1,], y[,2,], y[,3,], y[,4,])

umf1 <- unmarkedFrameGMM(y=y.ijst, numPrimary=T, type="removal")

(m1 <- gmultmix(~1, ~1, ~1, data=umf1, K=30))

backTransform(m1, type="lambda")      # Individuals per plot
backTransform(m1, type="phi")         # Probability of being available
(p <- backTransform(m1, type="det"))  # Probability of detection
p <- coef(p)

# Multinomial cell probabilities under removal design
c(p, (1-p) * p, (1-p)^2 * p)

# Or more generally:
head(getP(m1))

# Empirical Bayes estimates of super-population size
re <- ranef(m1)
plot(re, layout=c(5,5), xlim=c(-1,20), subset=site%in%1:25)

```

gpcount

Generalized binomial N-mixture model for repeated count data

Description

Fit the model of Chandler et al. (2011) to repeated count data collected using the robust design. This model allows for inference about population size, availability, and detection probability.

Usage

```

gpcount(lambdaformula, phiformula, pformula, data,
mixture = c("P", "NB"), K, starts, method = "BFGS", se = TRUE,
engine = c("C", "R"), ...)

```

Arguments

lambdaformula	Right-hand sided formula describing covariates of abundance.
phiformula	Right-hand sided formula describing availability covariates
pformula	Right-hand sided formula for detection probability covariates
data	An object of class unmarkedFrameGPC
mixture	Either "P" or "NB" for Poisson and negative binomial distributions
K	The maximum possible value of M, the super-population size.
starts	Starting values

method	Optimization method used by optim
se	Logical. Should standard errors be calculated?
engine	Either "C" or "R" for the C++ or R versions of the likelihood. The C++ code is faster, but harder to debug.
...	Additional arguments to optim , such as lower and upper bounds

Details

The latent transect-level super-population abundance distribution $f(M|\theta)$ can be set as either a Poisson or a negative binomial random variable, depending on the setting of the `mixture` argument. The expected value of M_i is λ_i . If $M_i \sim NB$, then an additional parameter, α , describes dispersion (lower α implies higher variance).

The number of individuals available for detection at time j is modeled as binomial: $N_{ij} \sim \text{Binomial}(M_i, \phi_{ij})$.

The detection process is also modeled as binomial: $y_{ikj} \sim \text{Binomial}(N_{ij}, p_{ikj})$.

Parameters λ , ϕ and p can be modeled as linear functions of covariates using the log, logit and logit links respectively.

Value

An object of class `unmarkedFitGPC`

Note

In the case where availability for detection is due to random temporary emigration, population density at time j , $D(i,j)$, can be estimated by $N(i,j)/\text{plotArea}$.

This model is also applicable to sampling designs in which the local population size is closed during the J repeated counts, and availability is related to factors such as the probability of vocalizing. In this case, density can be estimated by $M(i)/\text{plotArea}$.

If availability is a function of both temporary emigration and other processes such as song rate, then density cannot be directly estimated, but inference about the super-population size, $M(i)$, is possible.

Three types of covariates can be supplied, site-level, site-by-year-level, and observation-level. These must be formatted correctly when organizing the data with [unmarkedFrameGPC](#)

Author(s)

Richard Chandler <rbchan@uga.edu>

References

- Royle, J. A. 2004. N-Mixture models for estimating population size from spatially replicated counts. *Biometrics* 60:108–105.
- Chandler, R. B., J. A. Royle, and D. I. King. 2011. Inference about density and temporary emigration in unmarked populations. *Ecology* 92:1429–1435.

See Also

[gmultmix](#), [gdistsamp](#), [unmarkedFrameGPC](#)

Examples

```
set.seed(54)

nSites <- 20
nVisits <- 4
nReps <- 3

lambda <- 5
phi <- 0.7
p <- 0.5

M <- rpois(nSites, lambda) # super-population size

N <- matrix(NA, nSites, nVisits)
y <- array(NA, c(nSites, nReps, nVisits))
for(i in 1:nVisits) {
  N[,i] <- rbinom(nSites, M, phi) # population available during vist j
}
colMeans(N)

for(i in 1:nSites) {
  for(j in 1:nVisits) {
    y[i,,j] <- rbinom(nReps, N[i,j], p)
  }
}

ym <- matrix(y, nSites)
ym[1,] <- NA
ym[2, 1:nReps] <- NA
ym[3, (nReps+1):(nReps+nReps)] <- NA
umf <- unmarkedFrameGPC(y=ym, numPrimary=nVisits)

## Not run:
fmu <- gpcount(~1, ~1, ~1, umf, K=40, control=list(trace=TRUE, REPORT=1))

backTransform(fmu, type="lambda")
backTransform(fmu, type="phi")
backTransform(fmu, type="det")

## End(Not run)
```

Description

This function uses an ad-hoc averaging approach to impute missing entries in obsCovs. The missing entry is replaced by an average of the average for the site and the average for the visit number.

Usage

```
imputeMissing(umf, whichCovs = seq(length=ncol(obsCovs(umf))))
```

Arguments

umf	The data set who's obsCovs are being imputed.
whichCovs	An integer vector giving the indices of the covariates to be imputed. This defaults to all covariates in obsCovs.

Value

A version of umf that has the requested obsCovs imputed.

Author(s)

Ian Fiske

Examples

```
data(frogs)
pcru.obscovs <- data.frame(MinAfterSunset=as.vector(t(pcru.data[,1])),
  Wind=as.vector(t(pcru.data[,2])),
  Sky=as.vector(t(pcru.data[,3])),
  Temperature=as.vector(t(pcru.data[,4])))
pcruUMF <- unmarkedFrameOccu(y = pcru.bin, obsCovs = pcru.obscovs)
pcruUMF.i1 <- imputeMissing(pcruUMF)
pcruUMF.i2 <- imputeMissing(pcruUMF, whichCovs = 2)
```

issj	<i>Distance-sampling data for the Island Scrub Jay (Aphelocoma insularis)</i>
------	---

Description

Data were collected at 307 survey locations ("point transects") on Santa Cruz Island, California during the Fall of 2008. The distance data are binned into 3 distance intervals [0-100], (100-200], and (200-300]. The coordinates of the survey locations as well as 3 habitat covariates are also included.

Usage

```
data(issj)
```

Format

A data frame with 307 observations on the following 8 variables.

`issj[0-100]` Number of individuals detected within 100m

`issj(100-200]` Detections in the interval (100-200m]

`issj(200-300]` Detections in the interval (200-300m]

`x` Easting (meters)

`y` Northing (meters)

`elevation` Elevation in meters

`forest` Forest cover

`chaparral` Chaparral cover

References

Sillett, S. and Chandler, R.B. and Royle, J.A. and Kery, M. and Morrison, S.A. In Press. Hierarchical distance sampling models to estimate population size and habitat-specific abundance of an island endemic. *Ecological Applications*

See Also

Island-wide covariates are also available [cruz](#)

Examples

```
data(issj)
str(issj)
head(issj)

umf <- unmarkedFrameDS(y=as.matrix(issj[,1:3]), siteCovs=issj[,6:8],
  dist.breaks=c(0,100,200,300), unitsIn="m", survey="point")
summary(umf)
```

jay

European Jay data from the Swiss Breeding Bird Survey 2002

Description

The Swiss breeding bird survey ("Monitoring Haufige Brutvogel" MHB) has monitored the populations of 150 common species since 1999. The MHB sample consists of 267 1-km squares that are laid out as a grid across Switzerland. Fieldwork is conducted by about 200 skilled birdwatchers, most of them volunteers. Avian populations are monitored using a simplified territory mapping protocol, where each square is surveyed up to three times during the breeding season (only twice above the tree line). Surveys are conducted along a transect that does not change over the years.

The list `jay` has the data for European Jay territories for 238 sites surveyed in 2002.

Usage

```
data("jay")
```

Format

jay is a list with 3 elements:

caphist a data frame with rows for 238 sites and columns for each of the observable detection histories. For the sites visited 3 times, these are "100", "010", "001", "110", "101", "011", "111". Sites visited twice have "10x", "01x", "11x".

Each row gives the number of territories with the corresponding detection history, with NA for the detection histories not applicable: sites visited 3 times have NAs in the last 3 columns while those visited twice have NAs in the first 7 columns.

sitescovs a data frame with rows for 238 sites, and the following columns:

1. elev : the mean elevation of the quadrat, m.
2. length : the length of the route walked in the quadrat, km.
3. forest : percentage forest cover.

covinfo a data frame with rows for 238 sites, and the following columns:

1. x, y : the coordinates of the site.
2. date1, date2, date3 : the Julian date of the visit, with 1 April = 1. Sites visited twice have NA in the 3rd column.
3. dur1, dur2, dur3 : the duration of the survey, mins. For 10 visits the duration is not available, so there are additional NAs in these columns.

Note

In previous versions, jay had additional information not required for the analysis, and a data frame with essentially the same information as the Switzerland data set.

Source

Swiss Ornithological Institute

References

Royle, J.A., Kery, M., Gauthier, R., Schmid, H. (2007) Hierarchical spatial models of abundance and occurrence from imperfect survey data. *Ecological Monographs*, 77, 465-481.

Kery & Royle (2016) *Applied Hierarchical Modeling in Ecology* Section 7.9

Examples

```
data(jay)
str(jay)

# Carry out a simple analysis, without covariates:
# Create a customised piFun (see ?piFun for details)
crPiFun <- function(p) {
```

```

p1 <- p[,1] # Extract the columns of the p matrix, one for
p2 <- p[,2] # each of J = 3 sample occasions
p3 <- p[,3]
cbind(      # define multinomial cell probabilities:
  "100" = p1 * (1-p2) * (1-p3),
  "010" = (1-p1) * p2 * (1-p3),
  "001" = (1-p1) * (1-p2) * p3,
  "110" = p1 * p2 * (1-p3),
  "101" = p1 * (1-p2) * p3,
  "011" = (1-p1) * p2 * p3,
  "111" = p1 * p2 * p3,
  "10x" = p1*(1-p2),
  "01x" = (1-p1)*p2,
  "11x" = p1*p2)
}
# Build the unmarkedFrame object
mhb.umf <- unmarkedFrameMPois(y=as.matrix(jay$caphist),
  obsToY=matrix(1, 3, 10), piFun="crPiFun")
# Fit a model
( fm1 <- multinomPois(~1 ~1, mhb.umf) )

```

lambda2psi

Convert Poisson mean (lambda) to probability of occurrence (psi).

Description

Abundance and occurrence are fundamentally related.

Usage

```
lambda2psi(lambda)
```

Arguments

lambda Numeric vector with values ≥ 0

Value

A vector of psi values of the same length as lambda.

See Also

[pcount](#), [multinomPois](#), [distsamp](#)

Examples

```
lambda2psi(0:5)
```

linearComb-methods	<i>Methods for Function linearComb in Package ‘unmarked’</i>
--------------------	--

Description

Methods for function linearComb in Package ‘unmarked’

Methods

obj = "unmarkedEstimate", coefficients = "matrixOrVector" Typically called internally

obj = "unmarkedFit", coefficients = "matrixOrVector" Returns linear combinations of parameters from a fitted model. Coefficients are supplied through coefficients. The required argument type specifies which model estimate to use. You can use names(fittedmodel) to view possible values for the type argument.

Examples

```
data(ovendata)
ovenFrame <- unmarkedFrameMPois(ovendata.list$data,
  siteCovs=as.data.frame(scale(ovendata.list$covariates[,-1])), type = "removal")
fm <- multinomPois(~ 1 ~ ufc + trba, ovenFrame)
linearComb(fm, c(1, 0.5, 0.5), type = "state")
linearComb(fm, matrix(c(1, 0.5, 0.5, 1, 0, 0, 1, 0, 0.5), 3, 3,
  byrow=TRUE), type="state")
```

linetran	<i>Simulated line transect data</i>
----------	-------------------------------------

Description

Response matrix of animals detected in four distance classes plus transect lengths and two covariates.

Usage

```
data(linetran)
```

Format

A data frame with 12 observations on the following 7 variables.

dc1 Counts in distance class 1 [0-5 m)
 dc2 Counts in distance class 2 [5-10 m)
 dc3 Counts in distance class 3 [10-15 m)
 dc4 Counts in distance class 4 [15-20 m)
 Length Transect lengths in km
 area Numeric covariate
 habitat a factor with levels A and B

Examples

```
data(linetran)
linetran

# Format for distsamp()
ltUMF <- with(linetran, {
  unmarkedFrameDS(y = cbind(dc1, dc2, dc3, dc4),
    siteCovs = data.frame(Length, area, habitat),
    dist.breaks = c(0, 5, 10, 15, 20),
    tlength = linetran$Length * 1000, survey = "line", unitsIn = "m")
})
```

makePiFuns

Create functions to compute multinomial cell probabilities

Description

These are factory functions that generate piFuns with the required defaults, which are enclosed within the environment of the piFun. See the main entry for [piFuns](#).

Usage

```
makeRemPiFun(times)
makeCrPiFun(nOcc)
makeCrPiFunMb(nOcc)
makeCrPiFunMh(nOcc)
```

Arguments

times	a vector of times for each interval, length(times) is the number of survey occasions; can be all 1's if times are the same.
nOcc	the number of survey occasions

Details

makeRemPiFun produces a piFun for a removal model with the required number of occasions and potentially varying time intervals. The input to the piFun must be probabilities *per unit time*. This is a generalisation of the piFun in the Examples section of [piFuns](#).

makeCrPiFun produces a piFun for a standard capture-recapture model, M0, Mt or Mx. Probabilities of detection may vary across occasions. See Kery & Royle (2016) section 7.8.1.

makeCrPiFunMb produces a piFun for a capture-recapture model with a behavioral response after the first capture, Mb. Probabilities of detection are constant across occasions. The first column is the probability of detection for animals not caught before, column #2 is for animals after the first capture. The remaining columns are ignored. See Kery & Royle (2016) section 7.8.2.

makeCrPiFunMh produces a piFun for a capture-recapture model with individual heterogeneity in detection probability, Mh, using a logit-normal distribution. Probabilities of detection are constant

across occasions. The first column is the mean of the logit-normal on the probability scale. Cell `p[1, 2]` is a value in `[0, 1]` which controls the spread of the distribution. The remaining cells are ignored. See Kery & Royle (2016) section 7.8.3.

Value

A piFun with the appropriate defaults.

References

Kery, M., Royle, J. A. (2016) *Applied Hierarchical Modeling in Ecology* Vol 1.

Examples

```
# Generate piFuns and check their behaviour:

# makeRemPiFun
# =====
( pRem <- matrix(0.4, nrow=5, ncol=3) )
myPi <- makeRemPiFun(times=c(2,3,5))
myPi(pRem)
ls(environment(myPi)) # See what's in the environment
environment(myPi)$times

( pRem <- matrix(runif(15), 5, 3) )
myPi(pRem)

myPi <- makeRemPiFun(c(5,3,2))
environment(myPi)$times
myPi(pRem)

# More than 3 occasions
myPi <- makeRemPiFun(c(1,2,3,5))
try(myPi(pRem)) # Error
( pRem <- matrix(runif(20), 5, 4) )
myPi(pRem)
# Probability of escaping detection
1 - rowSums(myPi(pRem))

# makeCrPiFun
# =====
p <- matrix(0.4, 2, 3)
myPi <- makeCrPiFun(3)
myPi(p)
myPi # Look at the function
ls(environment(myPi))
environment(myPi)$histories

p <- matrix(runif(6, 0.1, 0.9), 2, 3) # different p's everywhere
myPi(p)

p <- matrix(runif(4*5, 0.1, 0.9), 4, 5) # > 3 occasions
```

```

try(myPi(p)) # Error
myPi <- makeCrPiFun(5)
( tmp <- myPi(p) )
1 - rowSums(tmp) # Probability of non-capture

# makeCrPiFunMb
# =====
( pMb <- cbind(rep(0.7, 5), 0.3, NA) )
myPi <- makeCrPiFunMb(3)
myPi(pMb)

( pMb <- matrix(runif(15), 5, 3) ) # col #3 will be ignored
myPi(pMb)

# with > 3 occasions
( pMb <- matrix(runif(15), 3, 5) )
try(myPi(pMb))
myPi <- makeCrPiFunMb(5)
myPi(pMb)

# makeCrPiFunMh
# =====
pMh <- cbind(rep(0.4, 5), NA, NA)
pMh[1, 2] <- 0.3
pMh
myPi <- makeCrPiFunMh(3)
myPi(pMh)
pMh <- cbind(runif(5), NA, NA)
pMh[1, 2] <- 0.3
pMh
myPi(pMh)

# with > 3 occasions
pMh <- cbind(runif(5), NA, NA, NA, NA)
pMh[1, 2] <- 0.3
pMh
try(myPi(pMh))
myPi <- makeCrPiFunMh(5)
1 - rowSums(myPi(pMh)) # Probability of non-detection

```

mallard

Mallard count data

Description

Mallard repeated count data and covariates

Usage

```
data(mallard)
```

Format

A list with 3 components

mallard.y response matrix

mallard.site site-specific covariates

mallard.obs survey-specific covariates

References

Kery, M., Royle, J. A., and Schmid, H. (2005) Modeling Avian Abundance from Replicated Counts Using Binomial Mixture Models. *Ecological Applications* 15(4), pp. 1450–1461.

Examples

```
data(mallard)
str(mallard.y)
str(mallard.site)
str(mallard.obs)
```

masspcru

Massachusetts North American Amphibian Monitoring Program Data

Description

masspcru contains NAAMP data for *Pseudacris crucifer* (pcru) in Massachusetts from 2001 to 2007 in the raw long format.

Usage

```
data(masspcru)
```

Format

Data frame with

SurveyYear Year of data collection.

RouteNumStopNum Stop number.

JulianDate Day of year.

Pcru Observed calling index.

MinAfterSunset Minutes after sunset of the observation.

Temperature Temperature measured during observation.

Details

These data come from the North American Amphibian Monitoring Program. Please see the reference below for more details.

Source

<https://www.pwrc.usgs.gov/naamp/>

References

Mossman MJ, Weir LA. North American Amphibian Monitoring Program (NAAMP). Amphibian Declines: the conservation status of United States species. University of California Press, Berkeley, California, USA. 2005:307-313.

Examples

```
data(masspcru)
str(masspcru)
```

modSel	<i>Model selection results from an unmarkedFitList</i>
--------	--

Description

Model selection results from an unmarkedFitList

Arguments

- object an object of class "unmarkedFitList" created by the function `fitList`.
- nullmod optional character naming which model in the `fitList` contains results from the null model. Only used in calculation of Nagelkerke's R-squared index.

Value

A S4 object with the following slots

- Full data.frame with formula, estimates, standard errors and model selection information. Converge is optim convergence code. CondNum is model condition number. n is the number of sites. delta is delta AIC. cumltvWt is cumulative AIC weight. Rsq is Nagelkerke's (1991) R-squared index, which is only returned when the nullmod argument is specified.
- Names matrix referencing column names of estimates (row 1) and standard errors (row 2).

Note

Two requirements exist to conduct AIC-based model-selection and model-averaging in unmarked. First, the data objects (ie, unmarkedFrames) must be identical among fitted models. Second, the response matrix must be identical among fitted models after missing values have been removed. This means that if a response value was removed in one model due to missingness, it needs to be removed from all models.

Author(s)

Richard Chandler <rbchan@uga.edu>

References

Nagelkerke, N.J.D. (2004) A Note on a General Definition of the Coefficient of Determination. *Biometrika* 78, pp. 691-692.

Examples

```
data(linetran)
(dbreaksLine <- c(0, 5, 10, 15, 20))
lengths <- linetran$Length * 1000

ltUMF <- with(linetran, {
  unmarkedFrameDS(y = cbind(dc1, dc2, dc3, dc4),
    siteCovs = data.frame(Length, area, habitat), dist.breaks = dbreaksLine,
    tlength = lengths, survey = "line", unitsIn = "m")
})

fm1 <- distsamp(~ 1 ~1, ltUMF)
fm2 <- distsamp(~ area ~1, ltUMF)
fm3 <- distsamp(~ 1 ~area, ltUMF)

f1 <- fitList(Null=fm1, A.=fm2, .A=fm3)
f1

ms <- modSel(f1, nullmod="Null")
ms

coef(ms)                # Estimates only
SE(ms)                   # Standard errors only
(toExport <- as(ms, "data.frame")) # Everything
```

multinomPois

Multinomial-Poisson Mixtures Model

Description

Fit the multinomial-Poisson mixture model to data collected using survey methods such as removal sampling or double observer sampling.

Usage

```
multinomPois(formula, data, starts, method = "BFGS",
  se = TRUE, engine=c("C", "R"), ...)
```

Arguments

formula	double right-hand side formula for detection and abundance covariates, in that order.
data	unmarkedFrame supplying data.
starts	vector of starting values.
method	Optimization method used by optim .
se	logical specifying whether or not to compute standard errors.
engine	Either "C" to use fast C++ code or "R" to use native R code during the optimization.
...	Additional arguments to optim, such as lower and upper bounds

Details

This function takes advantage of the closed form of the integrated likelihood when a latent Poisson distribution is assumed for abundance at each site and a multinomial distribution is taken for the observation state. Many common sampling methods can be framed in this context. For example, double-observer point counts and removal sampling can be analyzed with this function by specifying the proper multinomial cell probabilities. This is done with by supplying the appropriate function (piFun) argument. [removalPiFun](#) and [doublePiFun](#) are supplied as example cell probability functions.

Value

unmarkedFit object describing the model fit.

Author(s)

Ian Fiske

References

Royle, J. A. (2004). Generalized estimators of avian abundance from count survey data. *Animal Biodiversity and Conservation*, 27(1), 375-386.

Royle, J. A., & Dorazio, R. M. (2006). Hierarchical Models of Animal Abundance and Occurrence. *Journal Of Agricultural Biological And Environmental Statistics*, 11(3), 249.

See Also

[piFuns](#), [unmarkedFrameMPois](#)

Examples

```
# Simulate independent double observer data
nSites <- 50
lambda <- 10
p1 <- 0.5
p2 <- 0.3
```

```

cp <- c(p1*(1-p2), p2*(1-p1), p1*p2)
set.seed(9023)
N <- rpois(nSites, lambda)
y <- matrix(NA, nSites, 3)
for(i in 1:nSites) {
  y[i,] <- rmultinom(1, N[i], c(cp, 1-sum(cp)))[1:3]
}

# Fit model
observer <- matrix(c('A','B'), nSites, 2, byrow=TRUE)
umf <- unmarkedFrameMPois(y=y, obsCovs=list(observer=observer),
  type="double")
fm <- multinomPois(~observer-1 ~1, umf)

# Estimates of fixed effects
e <- coef(fm)
exp(e[1])
plogis(e[2:3])

# Estimates of random effects
re <- ranef(fm, K=20)
#ltheme <- canonical.theme(color = FALSE)
#lattice.options(default.theme = ltheme)
plot(re, layout=c(10,5))

## Real data
data(ovendata)
ovenFrame <- unmarkedFrameMPois(ovendata.list$data,
  siteCovs=as.data.frame(scale(ovendata.list$covariates[, -1])),
  type = "removal")
(fm1 <- multinomPois(~ 1 ~ ufc + trba, ovenFrame))

# Detection probability for a single pass
backTransform(fm1, type="det")

# Detection probability after 4 removal passes
rowSums(getP(fm1))

# Empirical Bayes estimates of abundance at first 25 sites
# Very low uncertainty because p is very high
plot(ranef(fm1, K=10), layout=c(10,7), xlim=c(-1, 10))

```

Description

Fit the model of Dail and Madsen (2011) and Hostetler and Chandler (2015) for designs involving repeated counts that yield multinomial outcomes. Possible data collection methods include repeated removal sampling and double observer sampling.

Usage

```
multmixOpen(lambdaformula, gammaformula, omegaformula, pformula,
  data, mixture=c("P", "NB", "ZIP"), K,
  dynamics=c("constant", "autoreg", "notrend", "trend", "ricker", "gompertz"),
  fix=c("none", "gamma", "omega"), immigration=FALSE, iotaformula = ~1,
  starts, method="BFGS", se=TRUE, ...)
```

Arguments

lambdaformula	Right-hand sided formula for initial abundance
gammaformula	Right-hand sided formula for recruitment rate (when dynamics is "constant", "autoreg", or "notrend") or population growth rate (when dynamics is "trend", "ricker", or "gompertz")
omegaformula	Right-hand sided formula for apparent survival probability (when dynamics is "constant", "autoreg", or "notrend") or equilibrium abundance (when dynamics is "ricker" or "gompertz")
pformula	A right-hand side formula describing the detection function covariates
data	An object of class unmarkedFrameMMO
mixture	String specifying mixture: "P", "NB", or "ZIP" for the Poisson, negative binomial, or zero-inflated Poisson distributions respectively
K	Integer defining upper bound of discrete integration. This should be higher than the maximum observed count and high enough that it does not affect the parameter estimates. However, the higher the value the slower the computation
dynamics	Character string describing the type of population dynamics. "constant" indicates that there is no relationship between omega and gamma. "autoreg" is an auto-regressive model in which recruitment is modeled as $\gamma * N[i, t-1]$. "notrend" model gamma as $\lambda * (1 - \omega)$ such that there is no temporal trend. "trend" is a model for exponential growth, $N[i, t] = N[i, t-1] * \gamma$, where gamma in this case is finite rate of increase (normally referred to as lambda). "ricker" and "gompertz" are models for density-dependent population growth. "ricker" is the Ricker-logistic model, $N[i, t] = N[i, t-1] * \exp(\gamma * (1 - N[i, t-1] / \omega))$, where gamma is the maximum instantaneous population growth rate (normally referred to as r) and omega is the equilibrium abundance (normally referred to as K). "gompertz" is a modified version of the Gompertz-logistic model, $N[i, t] = N[i, t-1] * \exp(\gamma * (1 - \log(N[i, t-1] + 1) / \log(\omega + 1)))$, where the interpretations of gamma and omega are similar to in the Ricker model
fix	If "omega", omega is fixed at 1. If "gamma", gamma is fixed at 0
immigration	Logical specifying whether or not to include an immigration term (iota) in population dynamics

iotaformula	Right-hand sided formula for average number of immigrants to a site per time step
starts	Vector of starting values
method	Optimization method used by optim
se	Logical specifying whether or not to compute standard errors
...	Additional arguments to optim, such as lower and upper bounds

Details

These models generalize multinomial N-mixture models (Royle et al. 2004) by relaxing the closure assumption (Dail and Madsen 2011, Hostetler and Chandler 2015, Sollmann et al. 2015).

The models include two or three additional parameters: gamma, either the recruitment rate (births and immigrations), the finite rate of increase, or the maximum instantaneous rate of increase; omega, either the apparent survival rate (deaths and emigrations) or the equilibrium abundance (carrying capacity); and iota, the number of immigrants per site and year. Estimates of population size at each time period can be derived from these parameters, and thus so can trend estimates. Or, trend can be estimated directly using dynamics="trend".

When immigration is set to FALSE (the default), iota is not modeled. When immigration is set to TRUE and dynamics is set to "autoreg", the model will separately estimate birth rate (gamma) and number of immigrants (iota). When immigration is set to TRUE and dynamics is set to "trend", "ricker", or "gompertz", the model will separately estimate local contributions to population growth (gamma and omega) and number of immigrants (iota).

The latent abundance distribution, $f(N|\theta)$ can be set as a Poisson, negative binomial, or zero-inflated Poisson random variable, depending on the setting of the mixture argument, mixture = "P", mixture = "NB", mixture = "ZIP" respectively. For the first two distributions, the mean of N_i is λ_i . If $N_i \sim NB$, then an additional parameter, α , describes dispersion (lower α implies higher variance). For the ZIP distribution, the mean is $\lambda_i(1 - \psi)$, where psi is the zero-inflation parameter.

For "constant", "autoreg", or "notrend" dynamics, the latent abundance state following the initial sampling period arises from a Markovian process in which survivors are modeled as $S_{it} \sim \text{Binomial}(N_{it-1}, \omega_{it})$, and recruits follow $G_{it} \sim \text{Poisson}(\gamma_{it})$. Alternative population dynamics can be specified using the dynamics and immigration arguments.

λ_i , γ_{it} , and ω_{it} are modeled using the the log link. p_{ijt} is modeled using the logit link. ω_{it} is either modeled using the logit link (for "constant", "autoreg", or "notrend" dynamics) or the log link (for "ricker" or "gompertz" dynamics). For "trend" dynamics, ω_{it} is not modeled.

The detection process is modeled as multinomial: $\mathbf{y}_{it} \sim \text{Multinomial}(N_{it}, \pi_{it})$, where π_{ijt} is the multinomial cell probability for plot i at time t on occasion j.

Options for the detection process include equal-interval removal sampling ("removal"), double observer sampling ("double"), or dependent double-observer sampling ("depDouble"). This option is specified when setting up the data using [unmarkedFrameMMO](#). Note that unlike the related functions [multinomPois](#) and [gmultmix](#), custom functions for the detection process (i.e., piFuns) are not supported. To request additional options contact the author.

Value

An object of class `unmarkedFitMMO`

Warning

This function can be extremely slow, especially if there are covariates of gamma or omega. Consider testing the timing on a small subset of the data, perhaps with `se=FALSE`. Finding the lowest value of `K` that does not affect estimates will also help with speed.

Note

When gamma or omega are modeled using year-specific covariates, the covariate data for the final year will be ignored; however, they must be supplied.

If the time gap between primary periods is not constant, an `M` by `T` matrix of integers should be supplied to `unmarkedFrameMMO` using the `primaryPeriod` argument.

Secondary sampling periods are optional, but can greatly improve the precision of the estimates.

Author(s)

Ken Kellner <contact@kenkellner.com>, Richard Chandler

References

Dail, D. and L. Madsen (2011) Models for Estimating Abundance from Repeated Counts of an Open Metapopulation. *Biometrics*. 67: 577-587.

Hostetler, J. A. and R. B. Chandler (2015) Improved State-space Models for Inference about Spatial and Temporal Variation in Abundance from Count Data. *Ecology* 96: 1713-1723.

Royle, J. A. (2004). Generalized estimators of avian abundance from count survey data. *Animal Biodiversity and Conservation* 27(1), 375-386.

See Also

`multinomPois`, `gmultmix`, `unmarkedFrameMMO`

Examples

```
#Generate some data
set.seed(123)
lambda=4; gamma=0.5; omega=0.8; p=0.5
M <- 100; T <- 5
y <- array(NA, c(M, 3, T))
N <- matrix(NA, M, T)
S <- G <- matrix(NA, M, T-1)

for(i in 1:M) {
  N[i,1] <- rpois(1, lambda)
  y[i,1,1] <- rbinom(1, N[i,1], p) # Observe some
  Nleft1 <- N[i,1] - y[i,1,1]     # Remove them
  y[i,2,1] <- rbinom(1, Nleft1, p) # ...
  Nleft2 <- Nleft1 - y[i,2,1]
  y[i,3,1] <- rbinom(1, Nleft2, p)
```

```

    for(t in 1:(T-1)) {
      S[i,t] <- rbinom(1, N[i,t], omega)
      G[i,t] <- rpois(1, gamma)
      N[i,t+1] <- S[i,t] + G[i,t]
      y[i,1,t+1] <- rbinom(1, N[i,t+1], p)    # Observe some
      Nleft1 <- N[i,t+1] - y[i,1,t+1]        # Remove them
      y[i,2,t+1] <- rbinom(1, Nleft1, p)    # ...
      Nleft2 <- Nleft1 - y[i,2,t+1]
      y[i,3,t+1] <- rbinom(1, Nleft2, p)
    }
  }
y=matrix(y, M)

#Create some random covariate data
sc <- data.frame(x1=rnorm(100))

#Create unmarked frame
umf <- unmarkedFrameMMO(y=y, numPrimary=5, siteCovs=sc, type="removal")

#Fit model
(fit <- multmixOpen(~x1, ~1, ~1, ~1, K=30, data=umf))

#Compare to truth
cf <- coef(fit)
data.frame(model=c(exp(cf[1]), cf[2], exp(cf[3]), plogis(cf[4]), plogis(cf[5])),
            truth=c(lambda, 0, gamma, omega, p))

#Predict
head(predict(fit, type='lambda'))

## Not run:
#Check fit with parametric bootstrap
pb <- parboot(fit, nsims=15)
plot(pb)

# Empirical Bayes estimates of abundance for each site / year
re <- ranef(fit)
plot(re, layout=c(10,5), xlim=c(-1, 10))

## End(Not run)

```

Description

Call `nonparboot` on an `unmarkedFit` to obtain non-parametric bootstrap samples. These can then be used by `vcov` in order to get bootstrap estimates of standard errors.

Details

Calling nonparboot on an unmarkedFit returns the original unmarkedFit, with the bootstrap samples added on. Then subsequent calls to `vcov` with the argument `method="nonparboot"` will use these bootstrap samples. Additionally, standard errors of derived estimates from either `linearComb` or `backTransform` can be instructed to use bootstrap samples by providing the argument `method="nonparboot"`.

For `occu` and `occuRN` both sites and occasions are re-sampled. For all other fitting functions, only sites are re-sampled.

Methods

`signature(object = "unmarkedFit")` Obtain nonparametric bootstrap samples for a general unmarkedFit.

`signature(object = "unmarkedFitColExt")` Obtain nonparametric bootstrap samples for colext fits.

`signature(object = "unmarkedFitDS")` Obtain nonparametric bootstrap samples for a distsamp fits.

`signature(object = "unmarkedFitMPois")` Obtain nonparametric bootstrap samples for a distsamp fits.

`signature(object = "unmarkedFitOccu")` Obtain nonparametric bootstrap samples for a occu fits.

`signature(object = "unmarkedFitOccuPEN")` Obtain nonparametric bootstrap samples for an occuPEN fit.

`signature(object = "unmarkedFitOccuPEN_CV")` Obtain nonparametric bootstrap samples for occuPEN_CV fit.

`signature(object = "unmarkedFitOccuRN")` Obtain nonparametric bootstrap samples for a occuRN fits.

`signature(object = "unmarkedFitPCount")` Obtain nonparametric bootstrap samples for a pcount fits.

Examples

```
data(ovendata)
ovenFrame <- unmarkedFrameMPois(ovendata.list$data,
siteCovs=as.data.frame(scale(ovendata.list$covariates[,-1])), type = "removal")
(fm <- multinomPois(~ 1 ~ ufc + trba, ovenFrame))
fm <- nonparboot(fm, B = 20) # should use larger B in real life.
vcov(fm, method = "hessian")
vcov(fm, method = "nonparboot")
avg.abundance <- backTransform(linearComb(fm, type = "state", coefficients = c(1, 0, 0)))

## Bootstrap sample information propagates through to derived quantities.
vcov(avg.abundance, method = "hessian")
vcov(avg.abundance, method = "nonparboot")
SE(avg.abundance, method = "nonparboot")
```


occu

*Fit the MacKenzie et al. (2002) Occupancy Model***Description**

This function fits the single season occupancy model of MacKenzie et al (2002).

Usage

```
occu(formula, data, knownOcc=numeric(0), linkPsi=c("logit", "cloglog"),
      starts, method="BFGS", se=TRUE, engine=c("C", "R"), ...)
```

Arguments

formula	Double right-hand side formula describing covariates of detection and occupancy in that order.
data	An unmarkedFrameOccu object
knownOcc	Vector of sites that are known to be occupied. These should be supplied as row numbers of the y matrix, eg, c(3,8) if sites 3 and 8 were known to be occupied a priori.
linkPsi	Link function for the occupancy model. Options are "logit" for the standard occupancy model or "cloglog" for the complimentary log-log link, which relates occupancy to site-level abundance. See details.
starts	Vector of parameter starting values.
method	Optimization method used by optim .
se	Logical specifying whether or not to compute standard errors.
engine	Either "C" or "R" to use fast C++ code or native R code during the optimization.
...	Additional arguments to optim, such as lower and upper bounds

Details

See [unmarkedFrame](#) and [unmarkedFrameOccu](#) for a description of how to supply data to the data argument.

occu fits the standard occupancy model based on zero-inflated binomial models (MacKenzie et al. 2006, Royle and Dorazio 2008). The occupancy state process (z_i) of site i is modeled as

$$z_i \sim \text{Bernoulli}(\psi_i)$$

The observation process is modeled as

$$y_{ij}|z_i \sim \text{Bernoulli}(z_i p_{ij})$$

By default, covariates of ψ_i and p_{ij} are modeled using the logit link according to the formula argument. The formula is a double right-hand sided formula like $\sim \text{detform} \sim \text{occform}$ where detform

is a formula for the detection process and occform is a formula for the partially observed occupancy state. See [formula](#) for details on constructing model formulae in R.

When `linkPsi = "cloglog"`, the complimentary log-log link function is used for *psi* instead of the logit link. The cloglog link relates occupancy probability to the intensity parameter of an underlying Poisson process (Kery and Royle 2016). Thus, if abundance at a site is can be modeled as $N_i \text{Poisson}(\lambda_i)$, where $\log(\lambda_i) = \alpha + \beta * x$, then presence/absence data at the site can be modeled as $Z_i \text{Binomial}(\psi_i)$ where $\text{cloglog}(\psi_i) = \alpha + \beta * x$.

Value

unmarkedFitOccu object describing the model fit.

Author(s)

Ian Fiske

References

- Kery, Marc, and J. Andrew Royle. 2016. *Applied Hierarchical Modeling in Ecology*, Volume 1. Academic Press.
- MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. Andrew Royle, and C. A. Langtimm. 2002. Estimating Site Occupancy Rates When Detection Probabilities Are Less Than One. *Ecology* 83: 2248-2255.
- MacKenzie, D. I. et al. 2006. *Occupancy Estimation and Modeling*. Amsterdam: Academic Press.
- Royle, J. A. and R. Dorazio. 2008. *Hierarchical Modeling and Inference in Ecology*. Academic Press.

See Also

[unmarked](#), [unmarkedFrameOccu](#), [modSel](#), [parboot](#)

Examples

```
data(frogs)
pferUMF <- unmarkedFrameOccu(pfer.bin)
plot(pferUMF, panels=4)
# add some fake covariates for illustration
siteCovs(pferUMF) <- data.frame(sitevar1 = rnorm(numSites(pferUMF)))

# observation covariates are in site-major, observation-minor order
obsCovs(pferUMF) <- data.frame(obsvar1 = rnorm(numSites(pferUMF) * obsNum(pferUMF)))

(fm <- occu(~ obsvar1 ~ 1, pferUMF))

confint(fm, type='det', method = 'normal')
confint(fm, type='det', method = 'profile')

# estimate detection effect at obsvars=0.5
(lc <- linearComb(fm['det'],c(1,0.5)))
```

```
# transform this to probability (0 to 1) scale and get confidence limits
(bt1c <- backTransform(lc))
confint(bt1c, level = 0.9)

# Empirical Bayes estimates of proportion of sites occupied
re <- ranef(fm)
sum(bup(re, stat="mode"))
```

occuFP	<i>Fit occupancy models when false positive detections occur (e.g., Royle and Link [2006] and Miller et al. [2011])</i>
--------	---

Description

This function fits the single season occupancy model while allowing for false positive detections.

Usage

```
occuFP(detformula = ~ 1, FPformula = ~ 1, Bformula = ~ 1,
stateformula = ~ 1, data, starts, method="BFGS", se = TRUE, engine = "R", ...)
```

Arguments

detformula	formula describing covariates of detection.
FPformula	formula describing covariates of false positive detection probability.
Bformula	formula describing covariates of probability detections are certain.
stateformula	formula describing covariates of occupancy.
data	An unmarkedFrameOccuFP object
starts	Vector of parameter starting values.
method	Optimization method used by optim .
se	Logical specifying whether or not to compute standard errors.
engine	Currently only choice is R.
...	Additional arguments to optim, such as lower and upper bounds

Details

See [unmarkedFrame](#) and [unmarkedFrameOccuFP](#) for a description of how to supply data to the data argument.

occuFP fits an extension of the standard single-season occupancy model (MacKenzie et al. 2002), which allows false positive detections. The occupancy status of a site is the same way as with the [occu](#) function, where stateformula is used to specify factors that lead to differences in occupancy probabilities among sites.

The observation process differs in that both false negative and false positive errors are modeled for observations. The function allows data to be of 3 types. These types are specified using in `unmarkedFrameOccuFP` as type. Occassions are specified to belong to 1 of the 3 data types and all or a subset of the data types can be combined in the same model.

For type 1 data, the detection process is assumed to fit the assumptions of the standard MacKenzie model where false negative probabilities are estimated but false positive detections are assumed not to occur. If all of your data is of this type you should use `codeoccu` to analyze data. The detection parameter p , which is modeled using the `detformula` is the only observation parameter for these data.

For type 2 data, both false negative and false positive detection probabilities are estimated. If all data is of this type the likelihood follows Royle and Link (2006). Both p (the true positive detection probability) and fp (the false positive detection probability described by `fpformula`) are estimated for occassions when this data type occurs

For type 3 data, observations are assumed to include both certain detections (false positives assumed not to occur) and uncertain detections that may include false positive detections. When only this data type occurs, the estimator is the same as the multiple detection state model described in Miller et al. (2011). Three observation parameters occur for this data type: p - true positive detection probability, fp - false positive detection probability, and b - the probability a true positive detection was designated as certain.

When both type 1 and type 2 data occur, the estimator is equivalent to the multiple detection method model described in Miller et al. (2011). The frog data example in the same paper uses an analysis where type 1 (dipnet surveys) and type 3 (call surveys) data were used.

Data in the y matrix of the unmarked frame should be all 0s and 1s for type 1 and type 2 data. For type 3 data, uncertain detections are given a value of 1 and certain detections a value of 2.

Value

`unmarkedFitOccuFP` object describing the model fit.

Author(s)

David Miller

References

- MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. Andrew Royle, and C. A. Langtimm. 2002. Estimating Site Occupancy Rates When Detection Probabilities Are Less Than One. *Ecology* 83: 2248-2255.
- Miller, D.A., J.D. Nichols, B.T. McClintock, E.H.C. Grant, L.L. Bailey, and L.A. Weir. 2011. Improving occupancy estimation when two types of observational error occur: non-detection and species misidentification. *Ecology* 92:1422-1428.
- Royle, J.A., and W.A. Link. 2006. Generalized site occupancy models allowing for false positive and false negative errors. *Ecology* 87:835-841.

See Also

[unmarked](#), [unmarkedFrameOccuFP](#), [modSel](#), [parboot](#)

Examples

```

n = 100
o = 10
o1 = 5
y = matrix(0,n,o)
p = .7
r = .5
fp = 0.05
y[1:(n*.5),(o-o1+1):o] <- rbinom((n*o1*.5),1,p)
y[1:(n*.5),1:(o-o1)] <- rbinom((o-o1)*n*.5,1,r)
y[(n*.5+1):n,(o-o1+1):o] <- rbinom((n*o1*.5),1,fp)
type <- c((o-o1),o1,0) ### vector with the number of each data type
site <- c(rep(1,n*.5*.8),rep(0,n*.5*.2),rep(1,n*.5*.2),rep(0,n*.8*.5))
occ <- matrix(c(rep(0,n*(o-o1)),rep(1,n*o1)),n,o)
site <- data.frame(habitat = site)
occ <- list(METH = occ)

umf1 <- unmarkedFrameOccuFP(y,site,occ, type = type)

m1 <- occuFP(detformula = ~ METH, FPformula = ~1,
             stateformula = ~ habitat, data = umf1)
predict(m1, type = 'fp')
coef(m1)
confint(m1, type = 'det')

```

 occuMS

Fit Single-Season and Dynamic Multi-State Occupancy Models

Description

This function fits single-season and dynamic multi-state occupancy models with both the multinomial and conditional binomial parameterizations.

Usage

```

occuMS(detformulas, psiformulas, phiformulas=NULL, data,
       parameterization=c("multinomial","condbinom"),
       starts, method="BFGS", se=TRUE, engine=c("C","R"), silent=FALSE, ...)

```

Arguments

detformulas	Character vector of formulas for detection probabilities. See details for a description of how to order these formulas.
psiformulas	Character vector of formulas for occupancy probabilities. See details for a description of how to order these formulas.

phiformulas	Character vector of formulas for state transition probabilities. Only used if you are fitting a dynamic model. See details for a description of how to order these formulas.
data	An <code>unmarkedFrameOccuMS</code> object
parameterization	Either "multinomial" for the multinomial parameterization (MacKenzie et al. 2009) which allows an arbitrary number of occupancy states, or "condbinom" for the conditional binomial parameterization (Nichols et al. 2007) which requires exactly 3 occupancy states. See details.
starts	Vector of parameter starting values.
method	Optimization method used by <code>optim</code> .
se	Logical specifying whether or not to compute standard errors.
engine	Either "C" to use fast C++ code or "R" to use native R code during the optimization.
silent	Boolean; if TRUE, suppress warnings.
...	Additional arguments to <code>optim</code> , such as lower and upper bounds

Details

Traditional occupancy models fit data with exactly two states: detection and non-detection (MacKenzie et al. 2002). The `occuMS` function fits models to occupancy data for which there are greater than 2 states (Nichols et al 2007, MacKenzie et al. 2009). For example, detections may be further divided into multiple biologically relevant categories, e.g. breeding vs. non-breeding, or some/many individuals present. As with detection status, classification of these additional occupancy states is likely to be imperfect.

Multiple parameterizations for multi-state occupancy models have been proposed. The `occuMS` function fits two at present: the "conditional binomial" parameterization of Nichols et al. (2007), and the more general "multinomial" parameterization of MacKenzie et al. (2009). Both single-season and dynamic models are possible with `occuMS` (MacKenzie et al. 2009).

The conditional binomial parameterization (`parameterization = 'condbinom'`) models occupancy and the presence or absence of an additional biological state of interest given the species is present (typically breeding status). Thus, there should be exactly 3 occupancy states in the data: 0 (non-detection); 1 (detection, no evidence of breeding); or 2 (detection, evidence of breeding).

Two state parameters are estimated: ψ , the probability of occupancy, and R , the probability of successful reproduction given an occupied state (although this could be some other binary biological condition). Covariates (in `siteCovs`) can be supplied for either or both of these parameters with the `stateformulas` argument, which takes a character vector of R-style formulas with length = 2, with formulas in the order (ψ , R). For example, to fit a model where ψ varies with a landcover covariate and R is constant, `stateformulas = c('~landcover', '~1')`.

There are three detection parameters associated with the conditional binomial parameterization: p_1 , the probability of detecting the species given true state 1; p_2 , the probability of detecting the species given true state 2; and δ , the probability of detecting state 2 (i.e., breeding), given that the species has been detected. See MacKenzie et al. (2009), pages 825-826 for more details. As with occupancy, covariates (in `obsCovs`) can be supplied for these detection probabilities with the `detformulas` argument, which takes a character vector of formulas with length = 3 in the order

(p_1, p_2, δ) . So, to fit a model where p_1 varies with temperature and the other two parameters are constant, `detformulas = c('~temp', '~1', '~1')`.

The multinomial parameterization (`parameterization = "multinomial"`) is more general, allowing an arbitrary number of occupancy states S . $S - 1$ occupancy probabilities ψ are estimated. Thus, if there are $S = 4$ occupancy states (0, 1, 2, 3), occuMS estimates ψ_1, ψ_2 , and ψ_3 (the probability of state 0 can be obtained by subtracting the others from 1). Covariates can be supplied for each occupancy probability with a character vector with length $S - 1$, e.g. `stateformulas = c('~landcover', '~1', '~1')` where ψ_1 varies with landcover and ψ_2 and ψ_3 are constant.

The number of detection probabilities estimated quickly expands as S increases, equal to $S \times (S - 1)/2$. In the simplest case (when $S = 3$), there are 3 detection probabilities: p_{11} , the probability of detecting state 1 given true state 1; p_{12} , the probability of detecting state 1 given true state 2; and p_{22} , the probability of detecting state 2 given true state 2. Covariates can be supplied for any or all of these detection probabilities with the `detformulas` argument, which takes a character vector of formulas with length = 3 in the order (p_{11}, p_{12}, p_{22}) . So, to fit a model where p_{11} varies with temperature and the other two detection probabilities are constant, `detformulas = c('~temp', '~1', '~1')`. If there were $S = 4$ occupancy states, there are 6 estimated detection probabilities and the order is $(p_{11}, p_{12}, p_{13}, p_{22}, p_{23}, p_{33})$, and so on. See MacKenzie et al. (2009) for a more detailed explanation.

Dynamic (multi-season) models can be fit as well for both parameterizations (MacKenzie et al. 2009). In a standard dynamic occupancy model, additional parameters for probabilities of colonization (i.e., state 0 \rightarrow 1) and extinction (1 \rightarrow 0) are estimated. In a multi-state context, we must estimate a transition probability matrix (ϕ) between all possible states. You can provide formulas for some of the probabilities in this matrix using the `phiformulas` argument. The approach differs depending on parameterization.

For the conditional binomial parameterization, `phiformulas` is a character vector of length 6. The first three elements are formulas for the probability a site is occupied at time t given that it was previously in states 0, 1, or 2 at time $t - 1$ (`phi0, phi1, phi2`). Elements 4-6 are formulas for the probability of reproduction (or other biological state) given state 0, 1, or 2 at time $t - 1$ (`R0, R1, R2`). See `umf@phiOrder$cond_binom` for a reminder of the correct order, where `umf` is your `unmarkedFrameOccuMS`.

For the multinomial parameterization, `phiformulas` can be used to provide formulas for some transitions between different occupancy states. You can't give formulas for the probabilities of remaining in the same state between seasons to keep the model identifiable. Thus, if there are 3 possible states (0, 1, 2), `phiformulas` should contain 6 formulas for the following transitions: `p(0->1), p(0->2), p(1->0), p(1->2), p(2->0), p(2->1)`, in that order (and similar for more than 3 states). The remaining probabilities of staying in the same state between seasons can be obtained via subtraction. See `umf@phiOrder$multinomial` for the correct order matching the number of states in your dataset.

See `unmarkedFrame` and `unmarkedFrameOccuMS` for a description of how to supply data to the `data` argument.

Value

`unmarkedFitOccuMS` object describing the model fit.

Author(s)

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References

MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. Andrew Royle, and C. A. Langtimm. 2002. Estimating Site Occupancy Rates When Detection Probabilities Are Less Than One. *Ecology* 83: 2248-2255.

MacKenzie, D. I., Nichols, J. D., Seamans, M. E., and R. J. Gutierrez, 2009. Modeling species occurrence dynamics with multiple states and imperfect detection. *Ecology* 90: 823-835.

Nichols, J. D., Hines, J. E., Mackenzie, D. I., Seamans, M. E., and R. J. Gutierrez. 2007. Occupancy estimation and modeling with multiple states and state uncertainty. *Ecology* 88: 1395-1400.

See Also

[unmarked](#), [unmarkedFrameOccuMS](#)

Examples

```
## Not run:

#Simulate data

#Parameters
N <- 500; J <- 5; S <- 3
site_covs <- matrix(rnorm(N*2),ncol=2)
obs_covs <- matrix(rnorm(N*J*2),ncol=2)
a1 <- -0.5; b1 <- 1; a2 <- -0.6; b2 <- -0.7

#####
## Multinomial parameterization ##
#####

p11 <- -0.4; p12 <- -1.09; p22 <- -0.84
truth <- c(a1,b1,a2,b2,p11,0,p12,p22)

#State process
lp <- matrix(NA,ncol=S,nrow=N)
for (n in 1:N){
  lp[n,2] <- exp(a1+b1*site_covs[n,1])
  lp[n,3] <- exp(a2+b2*site_covs[n,2])
  lp[n,1] <- 1
}
psi_mat <- lp/rowSums(lp)

z <- rep(NA,N)
for (n in 1:N){
  z[n] <- sample(0:2, 1, replace=T, prob=psi_mat[n,])
}
```



```

probs_raw <- matrix(c(1,0,0,1,exp(p11),0,1,exp(p12),exp(p22)),nrow=3,byrow=T)
probs_raw <- probs_raw/rowSums(probs_raw)

y <- matrix(0,nrow=N,ncol=J)
for (n in 1:N){

  probs <- switch(z[n]+1,
                 probs_raw[1,],
                 probs_raw[2,],
                 probs_raw[3,])
  if(z[n]>0){
    y[n,] <- sample(0:2, J, replace=T, probs)
  }
}

#Construct unmarkedFrame
umf <- unmarkedFrameOccuMS(y=y,siteCovs=as.data.frame(site_covs),
                           obsCovs=as.data.frame(obs_covs))

#Formulas

#3 states, so detformulas is a character vector of formulas of
#length 3 in following order:
#1) p[11]: prob of detecting state 1 given true state 1
#2) p[12]: prob of detecting state 1 given true state 2
#3) p[22]: prob of detecting state 2 given true state 2
detformulas <- c('~V1','~1','~1')
#If you had 4 states, it would be p[11],p[12],p[13],p[22],p[23],p[33] and so on

#3 states, so stateformulas is a character vector of length 2 in following order:
#1) psi[1]: probability of state 1
#2) psi[2]: probability of state 2
#You can get probability of state 0 (unoccupied) as 1 - psi[1] - psi[2]
stateformulas <- c('~V1','~V2')

#Fit model
fit <- occuMS(detformulas, stateformulas, data=umf,
              parameterization="multinomial")

#Look at results
fit
#Compare with truth
cbind(truth=truth,estimate=coef(fit))

#Generate predicted values
lapply(predict(fit,type='psi'),head)
lapply(predict(fit,type='det'),head)

#Fit a null model
detformulas <- rep('~1',3)
stateformulas <- rep('~1',2)
fit_null <- occuMS(detformulas, stateformulas, data=umf,
                  parameterization="multinomial")

```

```

#Compare fits
modSel(fitList(fit,fit_null))

#####
## Conditional binomial parameterization ##
#####

p11 <- 0.4; p12 <- 0.6; p22 <- 0.8
truth_cb <- c(a1,b1,a2,b2,qlogis(p11),0,qlogis(c(p12,p22)))

#Simulate data

#State process
psi_mat <- matrix(NA,ncol=S,nrow=N)
for (n in 1:N){
  psi_mat[n,2] <- plogis(a1+b1*site_covs[n,1])
  psi_mat[n,3] <- plogis(a2+b2*site_covs[n,2])
}
psi_bin <- matrix(NA,nrow=nrow(psi_mat),ncol=ncol(psi_mat))
psi_bin[,1] <- 1-psi_mat[,2]
psi_bin[,2] <- (1-psi_mat[,3])*psi_mat[,2]
psi_bin[,3] <- psi_mat[,2]*psi_mat[,3]
z <- rep(NA,N)
for (n in 1:N){
  z[n] <- sample(0:2, 1, replace=T, prob=psi_bin[n,])
}

#Detection process
y_cb <- matrix(0,nrow=N,ncol=J)
for (n in 1:N){
  #p11 = p1; p12 = p2; p22 = delta
  probs <- switch(z[n]+1,
                  c(1,0,0),
                  c(1-p11,p11,0),
                  c(1-p12,p12*(1-p22),p12*p22))
  if(z[n]>0){
    y_cb[n,] <- sample(0:2, J, replace=T, probs)
  }
}

#Build unmarked frame
umf2 <- unmarkedFrameOccuMS(y=y_cb,siteCovs=as.data.frame(site_covs),
                             obsCovs=as.data.frame(obs_covs))

#Formulas

#detformulas is a character vector of formulas of length 3 in following order:
#1) p[1]: prob of detecting species given true state 1
#2) p[2]: prob of detecting species given true state 2
#3) delta: prob of detecting state 2 (eg breeding) given species was detected
detformulas <- c('~V1','~1','~1')

```

```

#stateformulas is a character vector of length 2 in following order:
#1) psi: probability of occupancy
#2) R: probability state 2 (eg breeding) given occupancy
stateformulas <- c('~V1','~V2')

#Fit model
fit_cb <- occuMS(detformulas, stateformulas, data=umf2,
                 parameterization='condbinom')

#Look at results
fit_cb
#Compare with truth
cbind(truth=truth_cb,estimate=coef(fit_cb))

#Generate predicted values
lapply(predict(fit_cb,type='psi'),head)
lapply(predict(fit_cb,type='det'),head)

#####
## Dynamic (multi-season) model ##
#####

#Simulate data-----
N <- 500 #Number of sites
T <- 3 #Number of primary periods
J <- 5 #Number of secondary periods
S <- 3 #Number of occupancy states (0,1,2)

#Generate covariates
site_covs <- as.data.frame(matrix(rnorm(N*2),ncol=2))
yearly_site_covs <- as.data.frame(matrix(rnorm(N*T*2),ncol=2))
obs_covs <- as.data.frame(matrix(rnorm(N*J*T*2),ncol=2))

#True parameter values
b <- c(
  #Occupancy parameters
  a1=-0.5, b1=1, a2=-0.6, b2=-0.7,
  #Transition prob (phi) parameters
  phi01=0.7, phi01_cov=-0.5, phi02=-0.5, phi10=1.2,
  phi12=0.3, phi12_cov=1.1, phi20=-0.3, phi21=1.4, phi21_cov=0,
  #Detection prob parameters
  p11=-0.4, p11_cov=0, p12=-1.09, p22=-0.84
)

#Generate occupancy probs (multinomial parameterization)
lp <- matrix(1, ncol=S, nrow=N)
lp[,2] <- exp(b[1]+b[2]*site_covs[,1])
lp[,3] <- exp(b[3]+b[4]*site_covs[,2])
psi <- lp/rowSums(lp)

#True occupancy state matrix
z <- matrix(NA, nrow=N, ncol=T)

```

```

#Initial occupancy
for (n in 1:N){
  z[n,1] <- sample(0:(S-1), 1, prob=psi[n,])
}

#Raw phi probs
phi_raw <- matrix(NA, nrow=N*T, ncol=S^2-S)
phi_raw[,1] <- exp(b[5]+b[6]*yearly_site_covs[,1]) #p[0->1]
phi_raw[,2] <- exp(b[7]) #p[0->2]
phi_raw[,3] <- exp(b[8]) #p[1->0]
phi_raw[,4] <- exp(b[9]+b[10]*yearly_site_covs[,2]) #p[1->2]
phi_raw[,5] <- exp(b[11]) #p[2->0]
phi_raw[,6] <- exp(b[12]+b[13]*yearly_site_covs[,1])

#Generate states in times 2..T
px <- 1
for (n in 1:N){
  for (t in 2:T){
    phi_mat <- matrix(c(1, phi_raw[px,1], phi_raw[px,2], # phi|z=0
                        phi_raw[px,3], 1, phi_raw[px,4], # phi|z=1
                        phi_raw[px,5], phi_raw[px,6], 1), # phi|z=2
                      nrow=S, byrow=T)
    phi_mat <- phi_mat/rowSums(phi_mat)
    z[n, t] <- sample(0:(S-1), 1, prob=phi_mat[z[n,(t-1)]+1,])
    px <- px + 1
    if(t==T) px <- px + 1 #skip last datapoint for each site
  }
}

#Raw p probs
p_mat <- matrix(c(1, 0, 0, #p|z=0
                  1, exp(b[14]), 0, #p|z=1
                  1, exp(b[16]), exp(b[17])), #p|z=2
                nrow=S, byrow=T)
p_mat <- p_mat/rowSums(p_mat)

#Simulate observation data
y <- matrix(0, nrow=N, ncol=J*T)
for (n in 1:N){
  yx <- 1
  for (t in 1:T){
    if(z[n,t]==0){
      yx <- yx + J
      next
    }
    for (j in 1:J){
      y[n, yx] <- sample(0:(S-1), 1, prob=p_mat[z[n,t]+1,])
      yx <- yx+1
    }
  }
}
#-----

```

```

#Model fitting

#Build UMF
umf <- unmarkedFrameOccuMS(y=y, siteCovs=site_covs,
                           obsCovs=obs_covs,
                           yearlySiteCovs=yearly_site_covs,
                           numPrimary=3)

summary(umf)

#Formulas
#Initial occupancy
psiformulas <- c('~V1','~V2') #on psi[1] and psi[2]

#Transition probs
#Guide to order:
umf@phiOrder$multinomial
phiformulas <- c('~V1','~1','~1','~V2','~1','~V1')

#Detection probability
detformulas <- c('~V1','~1','~1') #on p[1|1], p[1|2], p[2|2]

#Fit model
(fit <- occuMS(detformulas=detformulas, psiformulas=psiformulas,
              phiformulas=phiformulas, data=umf))

#Compare with truth
compare <- cbind(b,coef(fit),
                 coef(fit)-1.96*SE(fit),coef(fit)+1.96*SE(fit))
colnames(compare) <- c('truth','estimate','lower','upper')
round(compare,3)

#Estimated phi matrix for site 1
phi_est <- predict(fit, 'phi', se.fit=F)
phi_est <- sapply(phi_est, function(x) x$Predicted[1])
phi_est_mat <- matrix(NA, nrow=S, ncol=S)
phi_est_mat[c(4,7,2,8,3,6)] <- phi_est
diag(phi_est_mat) <- 1 - rowSums(phi_est_mat,na.rm=T)

#Actual phi matrix for site 1
phi_act_mat <- diag(S)
phi_act_mat[c(4,7,2,8,3,6)] <- phi_raw[1,]
phi_act_mat <- phi_act_mat/rowSums(phi_act_mat)

#Compare
cat('Estimated phi\n')
phi_est_mat
cat('Actual phi\n')
phi_act_mat

#Rough check of model fit
fit_sim <- simulate(fit, nsim=20)
hist(sapply(fit_sim,mean),col='gray')

```

```
abline(v=mean(umf@y),col='red',lwd=2)
#line should fall near middle of histogram

## End(Not run)
```

occuMulti

Fit the Rota et al. (2016) Multi-species Occupancy Model

Description

This function fits the multispecies occupancy model of Rota et al (2016).

Usage

```
occuMulti(detformulas, stateformulas, data, maxOrder, starts, method="BFGS",
          se=TRUE, engine=c("C","R"), silent=FALSE, ...)
```

Arguments

detformulas	Character vector of formulas for the detection models, one per species.
stateformulas	Character vector of formulas for the natural parameters. To fix a natural parameter at 0, specify the corresponding formula as " \emptyset " or " $\sim\emptyset$ ".
data	An <code>unmarkedFrameOccuMulti</code> object
maxOrder	Optional; specify maximum interaction order. Defaults to number of species (all possible interactions). Reducing this value may speed up optimization if you aren't interested in higher-order interactions.
starts	Vector of parameter starting values.
method	Optimization method used by <code>optim</code> .
se	Logical specifying whether or not to compute standard errors.
engine	Either "C" to use fast C++ code or "R" to use native R code during the optimization.
silent	Boolean; if TRUE, suppress warnings.
...	Additional arguments to <code>optim</code> , such as lower and upper bounds

Details

See `unmarkedFrame` and `unmarkedFrameOccuMulti` for a description of how to supply data to the data argument.

`occuMulti` fits the multispecies occupancy model from Rota et al. (2016), for two or more interacting species. The model generalizes the standard single-species occupancy model from MacKenzie et al. (2002). The latent occupancy state at site i for a set of s potentially interacting species is a vector \mathbf{Z}_i of length s containing a sequence of the values 0 or 1. For example, when $s = 2$, the possible states are [11], [10], [01], or [00], corresponding to both species present, only species 1 or

species 2 present, or both species absent, respectively. The latent state modeled as a multivariate Bernoulli random variable:

$$\mathbf{Z}_i \sim \text{MVB}(\boldsymbol{\psi}_i)$$

where $\boldsymbol{\psi}_i$ is a vector of length 2^s containing the probability of each possible combination of 0s and 1s, such that $\sum \boldsymbol{\psi}_i = 1$.

For $s = 2$, the corresponding natural parameters f are

$$f_1 = \log \left(\frac{\psi_{10}}{\psi_{00}} \right)$$

$$f_2 = \log \left(\frac{\psi_{01}}{\psi_{00}} \right)$$

$$f_{12} = \log \left(\frac{\psi_{11}\psi_{00}}{\psi_{10}\psi_{01}} \right)$$

The natural parameters can then be modeled as linear functions of covariates. Covariates for each f must be specified with the `stateformulas` argument, which takes a character vector of individual formulas of length equal to the number of natural parameters (which in turn depends on the number of species in the model).

The observation process is similar to the standard single-species occupancy model, except that the observations \mathbf{y}_{ij} at site i on occasion j are vectors of length s and there are independent values of detection probability p for each species s :

$$\mathbf{y}_{ij} | \mathbf{Z}_i \sim \text{MVB}(\mathbf{Z}_i \mathbf{p}_{sij})$$

Independent detection models (potentially containing different covariates) must be provided for each species with the `detformulas` argument, which takes a character vector of individual formulas with length equal to the number of species s .

Value

unmarkedFitOccuMulti object describing the model fit.

Author(s)

Ken Kellner <contact@kenkellner.com>

References

- MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. Andrew Royle, and C. A. Langtimm. 2002. Estimating Site Occupancy Rates When Detection Probabilities Are Less Than One. *Ecology* 83: 2248-2255.
- Rota, C.T., et al. 2016. A multi-species occupancy model for two or more interacting species. *Methods in Ecology and Evolution* 7: 1164-1173.

See Also

[unmarked](#), [unmarkedFrameOccuMulti](#)

Examples

```
## Not run:
#Simulate 3 species data
N <- 1000
nspecies <- 3
J <- 5

occ_covs <- as.data.frame(matrix(rnorm(N * 10),ncol=10))
names(occ_covs) <- paste('occ_cov',1:10,sep='')

det_covs <- list()
for (i in 1:nspecies){
  det_covs[[i]] <- matrix(rnorm(N*J),nrow=N)
}
names(det_covs) <- paste('det_cov',1:nspecies,sep='')

#True vals
beta <- c(0.5,0.2,0.4,0.5,-0.1,-0.3,0.2,0.1,-1,0.1)
f1 <- beta[1] + beta[2]*occ_covs$occ_cov1
f2 <- beta[3] + beta[4]*occ_covs$occ_cov2
f3 <- beta[5] + beta[6]*occ_covs$occ_cov3
f4 <- beta[7]
f5 <- beta[8]
f6 <- beta[9]
f7 <- beta[10]
f <- cbind(f1,f2,f3,f4,f5,f6,f7)
z <- expand.grid(rep(list(1:0),nspecies))[,nspecies:1]
colnames(z) <- paste('sp',1:nspecies,sep='')
dm <- model.matrix(as.formula(paste0("~.^",nspecies,"-1")),z)

psi <- exp(f %*% t(dm))
psi <- psi/rowSums(psi)

#True state
ztruth <- matrix(NA,nrow=N,ncol=nspecies)
for (i in 1:N){
  ztruth[i,] <- as.matrix(z[sample(8,1,prob=psi[i,]),])
}

p_true <- c(0.6,0.7,0.5)

# fake y data
y <- list()

for (i in 1:nspecies){
  y[[i]] <- matrix(NA,N,J)
  for (j in 1:N){
```



```

    for (k in 1:J){
      y[[i]][j,k] <- rbinom(1,1,ztruth[j,i]*p_true[i])
    }
  }
}
names(y) <- c('coyote','tiger','bear')

#Create the unmarked data object
data = unmarkedFrameOccuMulti(y=y,siteCovs=occ_covs,obsCovs=det_covs)

#Summary of data object
summary(data)
plot(data)

# Look at f parameter design matrix
data@fDesign

# Formulas for state and detection processes

# Length should match number/order of columns in fDesign
occFormulas <- c('~occ_cov1','~occ_cov2','~occ_cov3','~1','~1','~1','~1')

#Length should match number/order of species in data@ylist
detFormulas <- c('~1','~1','~1')

fit <- occuMulti(detFormulas,occFormulas,data)

#Look at output
fit

plot(fit)

#Compare with known values
cbind(c(beta,log(p_true/(1-p_true))),fit@opt$par)

#predict method
lapply(predict(fit,'state'),head)
lapply(predict(fit,'det'),head)

#marginal occupancy
head(predict(fit,'state',species=2))
head(predict(fit,'state',species='bear'))
head(predict(fit,'det',species='coyote'))

#probability of co-occurrence of two or more species
head(predict(fit, 'state', species=c('coyote','tiger'))))

#conditional occupancy
head(predict(fit,'state',species=2,cond=3)) #tiger | bear present
head(predict(fit,'state',species='tiger',cond='bear')) #tiger | bear present
head(predict(fit,'state',species='tiger',cond='-bear')) #bear absent
head(predict(fit,'state',species='tiger',cond=c('coyote','-bear'))))

```

```

#residuals (by species)
lapply(residuals(fit),head)

#ranef (by species)
ranef(fit, species='coyote')

#parametric bootstrap
bt <- parboot(fit,nsim=30)

#update model
occFormulas <- c('~occ_cov1','~occ_cov2','~occ_cov2+occ_cov3','~1','~1','~1','~1')
fit2 <- update(fit,stateformulas=occFormulas)

#List of fitted models
fl <- fitList(fit,fit2)
coef(fl)

#Model selection
modSel(fl)

#Fit model while forcing some natural parameters to be 0
#For example: fit model with no species interactions
occFormulas <- c('~occ_cov1','~occ_cov2','~occ_cov2+occ_cov3','0','0','0','0')
fit3 <- occuMulti(detFormulas,occFormulas,data)

#Alternatively, you can force all interaction parameters above a certain
#order to be zero with maxOrder. This will be faster.
occFormulas <- c('~occ_cov1','~occ_cov2','~occ_cov2+occ_cov3')
fit4 <- occuMulti(detFormulas,occFormulas,data,maxOrder=1)

## End(Not run)

```

occuPEN

Fit the MacKenzie et al. (2002) Occupancy Model with the penalized likelihood methods of Hutchinson et al. (2015)

Description

This function fits the occupancy model of MacKenzie et al (2002) with the penalized methods of Hutchinson et al (2015).

Usage

```
occuPEN(formula, data, knownOcc=numeric(0), starts, method="BFGS",
        engine=c("C", "R"), lambda=0, pen.type = c("Bayes","Ridge","MPLE"), ...)
```

Arguments

formula	Double right-hand side formula describing covariates of detection and occupancy in that order.
data	An unmarkedFrameOccu object
knownOcc	Vector of sites that are known to be occupied. These should be supplied as row numbers of the y matrix, eg, c(3,8) if sites 3 and 8 were known to be occupied a priori.
starts	Vector of parameter starting values.
method	Optimization method used by optim .
engine	Either "C" or "R" to use fast C++ code or native R code during the optimization.
lambda	Penalty weight parameter.
pen.type	Which form of penalty to use.
...	Additional arguments to optim, such as lower and upper bounds

Details

See [unmarkedFrame](#) and [unmarkedFrameOccu](#) for a description of how to supply data to the data argument.

occuPEN fits the standard occupancy model based on zero-inflated binomial models (MacKenzie et al. 2006, Royle and Dorazio 2008) using the penalized likelihood methods described in Hutchinson et al. (2015). See [occu](#) for model details. occuPEN returns parameter estimates that maximize a penalized likelihood in which the penalty is specified by the pen.type argument. The penalty function is weighted by lambda.

The MPLE method includes an equation for computing lambda (Moreno & Lele, 2010). If the value supplied does not equal match the one computed with this equation, the supplied value is used anyway (with a warning).

Value

unmarkedFitOccuPEN object describing the model fit.

Author(s)

Rebecca A. Hutchinson

References

- Hutchinson, R. A., J. V. Valente, S. C. Emerson, M. G. Betts, and T. G. Dietterich. 2015. Penalized Likelihood Methods Improve Parameter Estimates in Occupancy Models. *Methods in Ecology and Evolution*. DOI: 10.1111/2041-210X.12368
- MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. Andrew Royle, and C. A. Langtimm. 2002. Estimating Site Occupancy Rates When Detection Probabilities Are Less Than One. *Ecology* 83: 2248-2255.
- MacKenzie, D. I. et al. 2006. *Occupancy Estimation and Modeling*. Amsterdam: Academic Press.

Moreno, M. and S. R. Lele. 2010. Improved estimation of site occupancy using penalized likelihood. *Ecology* 91: 341-346.

Royle, J. A. and R. Dorazio. 2008. *Hierarchical Modeling and Inference in Ecology*. Academic Press.

See Also

[unmarked](#), [unmarkedFrameOccu](#), [occu](#), [computeMPLElambda](#), [occuPEN_CV](#), [nonparboot](#)

Examples

```
# Simulate occupancy data
set.seed(344)
nSites <- 100
nReps <- 2
covariates <- data.frame(vegtht=rnorm(nSites),
  habitat=factor(c(rep('A', nSites/2), rep('B', nSites/2))))

psipars <- c(-1, 1, -1)
ppars <- c(1, -1, 0)
X <- model.matrix(~vegtht+habitat, covariates) # design matrix
psi <- plogis(X %*% psipars)
p <- plogis(X %*% ppars)

y <- matrix(NA, nSites, nReps)
z <- rbinom(nSites, 1, psi)      # true occupancy state
for(i in 1:nSites) {
  y[i,] <- rbinom(nReps, 1, z[i]*p[i])
}

# Organize data and look at it
umf <- unmarkedFrameOccu(y = y, siteCovs = covariates)
obsCovs(umf) <- covariates
head(umf)
summary(umf)

# Fit some models
fmMLE <- occu(~vegtht+habitat ~vegtht+habitat, umf)
fm1pen <- occuPEN(~vegtht+habitat ~vegtht+habitat, umf, lambda=0.33, pen.type="Ridge")
fm2pen <- occuPEN(~vegtht+habitat ~vegtht+habitat, umf, lambda=1, pen.type="Bayes")

# MPLE:
fm3pen <- occuPEN(~vegtht+habitat ~vegtht+habitat, umf, lambda=0.5, pen.type="MPLE")
MPLElambda = computeMPLElambda(~vegtht+habitat ~vegtht+habitat, umf)
fm4pen <- occuPEN(~vegtht+habitat ~vegtht+habitat, umf, lambda=MPLElambda, pen.type="MPLE")

# nonparametric bootstrap for uncertainty analysis:
fm1pen <- nonparboot(fm1pen, B=20) # should use more samples
vcov(fm1pen, method="nonparboot")
```

occuPEN_CV	<i>Fit the MacKenzie et al. (2002) Occupancy Model with the penalized likelihood methods of Hutchinson et al. (2015) using cross-validation</i>
------------	---

Description

This function fits the occupancy model of MacKenzie et al (2002) with the penalized methods of Hutchinson et al (2015) using k-fold cross-validation to choose the penalty weight.

Usage

```
occuPEN_CV(formula, data, knownOcc=numeric(0), starts, method="BFGS",
  engine=c("C", "R"), lambdaVec=c(0,2^seq(-4,4)),
  pen.type = c("Bayes","Ridge"), k = 5, foldAssignments = NA,
  ...)
```

Arguments

formula	Double right-hand side formula describing covariates of detection and occupancy in that order.
data	An unmarkedFrameOccu object
knownOcc	Vector of sites that are known to be occupied. These should be supplied as row numbers of the y matrix, eg, c(3,8) if sites 3 and 8 were known to be occupied a priori.
starts	Vector of parameter starting values.
method	Optimization method used by optim .
engine	Either "C" or "R" to use fast C++ code or native R code during the optimization.
lambdaVec	Vector of values to try for lambda.
pen.type	Which form of penalty to use.
k	Number of folds for k-fold cross-validation.
foldAssignments	Vector containing the number of the fold that each site falls into. Length of the vector should be equal to the number of sites, and the vector should contain k unique values. E.g. for 9 sites and 3 folds, c(1,2,3,1,2,3,1,2,3) or c(1,1,1,2,2,2,3,3,3).
...	Additional arguments to optim, such as lower and upper bounds

Details

See [unmarkedFrame](#) and [unmarkedFrameOccu](#) for a description of how to supply data to the data argument.

This function wraps k-fold cross-validation around `occuPEN_CV` for the "Bayes" and "Ridge" penalties of Hutchinson et al. (2015). The user may specify the number of folds (k), the values to try (`lambdaVec`), and the assignments of sites to folds (`foldAssignments`). If `foldAssignments` is not provided, the assignments are done pseudo-randomly, and the function attempts to put some sites with and without positive detections in each fold. This randomness introduces variability into the results of this function across runs; to eliminate the randomness, supply `foldAssignments`.

Value

`unmarkedFitOccuPEN_CV` object describing the model fit.

Author(s)

Rebecca A. Hutchinson

References

Hutchinson, R. A., J. V. Valente, S. C. Emerson, M. G. Betts, and T. G. Dietterich. 2015. Penalized Likelihood Methods Improve Parameter Estimates in Occupancy Models. *Methods in Ecology and Evolution*. DOI: 10.1111/2041-210X.12368

MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. Andrew Royle, and C. A. Langtimm. 2002. Estimating Site Occupancy Rates When Detection Probabilities Are Less Than One. *Ecology* 83: 2248-2255.

See Also

[unmarked](#), [unmarkedFrameOccu](#), [occu](#), [occuPEN](#), [nonparboot](#)

Examples

```
# Simulate occupancy data
set.seed(646)
nSites <- 60
nReps <- 2
covariates <- data.frame(veght=rnorm(nSites),
  habitat=factor(c(rep('A', 30), rep('B', 30))))

psipars <- c(-1, 1, -1)
ppars <- c(1, -1, 0)
X <- model.matrix(~veght+habitat, covariates) # design matrix
psi <- plogis(X %*% psipars)
p <- plogis(X %*% ppars)

y <- matrix(NA, nSites, nReps)
z <- rbinom(nSites, 1, psi)      # true occupancy state
for(i in 1:nSites) {
```

```

      y[i,] <- rbinom(nReps, 1, z[i]*p[i])
    }

# Organize data and look at it
umf <- unmarkedFrameOccu(y = y, siteCovs = covariates)
obsCovs(umf) <- covariates
head(umf)
summary(umf)

## Not run:

# Fit some models
fmMLE <- occu(~veght+habitat ~veght+habitat, umf)
fmMLE@estimates

fm1penCV <- occuPEN_CV(~veght+habitat ~veght+habitat,
  umf, pen.type="Ridge", foldAssignments=rep(1:5, ceiling(nSites/5))[1:nSites])
fm1penCV@lambdaVec
fm1penCV@chosenLambda
fm1penCV@estimates

fm2penCV <- occuPEN_CV(~veght+habitat ~veght+habitat,
  umf, pen.type="Bayes", foldAssignments=rep(1:5, ceiling(nSites/5))[1:nSites])
fm2penCV@lambdaVec
fm2penCV@chosenLambda
fm2penCV@estimates

# nonparametric bootstrap for uncertainty analysis:
# bootstrap is wrapped around the cross-validation
fm2penCV <- nonparboot(fm2penCV, B=10) # should use more samples
vcov(fm2penCV, method="nonparboot")

# Mean squared error of parameters:
mean((c(psipars, ppars) - c(fmMLE[1]@estimates, fmMLE[2]@estimates))^2)
mean((c(psipars, ppars) - c(fm1penCV[1]@estimates, fm1penCV[2]@estimates))^2)
mean((c(psipars, ppars) - c(fm2penCV[1]@estimates, fm2penCV[2]@estimates))^2)

## End(Not run)

```

Description

Fit the occupancy model of Royle and Nichols (2003), which relates probability of detection of the species to the number of individuals available for detection at each site. Probability of occupancy is a derived parameter: the probability that at least one individual is available for detection at the site.

Usage

```
occuRN(formula, data, K=25, starts, method="BFGS", se=TRUE, engine=c("C", "R"), ...)
```

Arguments

formula	double right-hand side formula describing covariates of detection and abundance, in that order.
data	Object of class <code>unmarkedFrameOccu</code> supplying data to the model.
K	the upper summation index used to numerically integrate out the latent abundance. This should be set high enough so that it does not affect the parameter estimates. Computation time will increase with K.
starts	initial values for the optimization.
method	Optimization method used by <code>optim</code> .
se	logical specifying whether or not to compute standard errors.
engine	Either "C" to use fast C++ code or "R" to use native R code during the optimization.
...	Additional arguments to <code>optim</code> , such as lower and upper bounds

Details

This function fits the latent abundance mixture model described in Royle and Nichols (2003).

The number of animals available for detection at site i is modelled as Poisson:

$$N_i \sim \text{Poisson}(\lambda_i)$$

We assume that all individuals at site i during sample j have identical detection probabilities, r_{ij} , and that detections are independent. The species will be recorded if at least one individual is detected. Thus, the detection probability for the species is linked to the detection probability for an individual by

$$p_{ij} = 1 - (1 - r_{ij})^{N_i}$$

Note that if $N_i = 0$, then $p_{ij} = 0$, and increasing values of N_i lead to higher values of p_{ij} . The equation for the detection history is then:

$$y_{ij} \sim \text{Bernoulli}(p_{ij})$$

Covariates of λ_i are modelled with the log link and covariates of r_{ij} are modelled with the logit link.

Value

`unmarkedFit` object describing the model fit.

Author(s)

Ian Fiske

References

Royle, J. A. and Nichols, J. D. (2003) Estimating Abundance from Repeated Presence-Absence Data or Point Counts. *Ecology*, 84(3) pp. 777–790.

Examples

```
## Not run:

data(birds)
woodthrushUMF <- unmarkedFrameOccu(woodthrush.bin)
# survey occasion-specific detection probabilities
(fm.wood.rn <- occuRN(~ obsNum ~ 1, woodthrushUMF))

# Empirical Bayes estimates of abundance at each site
re <- ranef(fm.wood.rn)
plot(re)

## End(Not run)
```

occuTTD

*Fit Single-Season and Dynamic Time-to-detection Occupancy Models***Description**

Fit time-to-detection occupancy models of Garrard et al. (2008, 2013), either single-season or dynamic. Time-to-detection can be modeled with either an exponential or Weibull distribution.

Usage

```
occuTTD(psiformula= ~1, gammaformula = ~ 1, epsilonformula = ~ 1,
  detformula = ~ 1, data, ttdDist = c("exp", "weibull"),
  linkPsi = c("logit", "cloglog"), starts, method="BFGS", se=TRUE,
  engine = c("C", "R"), ...)
```

Arguments

psiformula Right-hand sided formula for the initial probability of occupancy at each site.

gammaformula Right-hand sided formula for colonization probability.

epsilonformula Right-hand sided formula for extinction probability.

detformula	Right-hand sided formula for mean time-to-detection.
data	unmarkedFrameOccuTTD object that supplies the data (see unmarkedFrameOccuTTD).
ttdDist	Distribution to use for time-to-detection; either "exp" for the exponential, or "weibull" for the Weibull, which adds an additional shape parameter k .
linkPsi	Link function for the occupancy model. Options are "logit" for the standard occupancy model or "cloglog" for the complimentary log-log link, which relates occupancy to site-level abundance.
starts	optionally, initial values for parameters in the optimization.
method	Optimization method used by optim .
se	logical specifying whether or not to compute standard errors.
engine	Either "C" or "R" to use fast C++ code or native R code during the optimization.
...	Additional arguments to optim, such as lower and upper bounds

Details

Estimates site occupancy and detection probability from time-to-detection (TTD) data, e.g. time to first detection of a particular bird species during a point count or time-to-detection of a plant species while searching a quadrat (Garrard et al. 2008). Time-to-detection can be modeled as an exponential (`ttdDist="exp"`) or Weibull (`ttdDist="weibull"`) random variable with rate parameter λ and, for the Weibull, an additional shape parameter k . Note that `occuTTD` puts covariates on λ and not $1/\lambda$, i.e., the expected time between events.

In the case where there are no detections before the maximum sample time at a site (`surveyLength`) is reached, we are not sure if the site is unoccupied or if we just didn't wait long enough for a detection. We therefore must censor the exponential or Weibull distribution at the maximum survey length, $Tmax$. Thus, assuming true site occupancy at site i is z_i , an exponential distribution for the TTD y_i , and that $d_i = 1$ indicates y_i is censored (Kery and Royle 2016):

$$d_i = z_i * I(y_i > Tmax_i) + (1 - z_i)$$

and

$$y_i | z_i \sim Exponential(\lambda_i), d_i = 0$$

$$y_i | z_i = Missing, d_i = 1$$

Because in unmarked values of NA are typically used to indicate missing values that were a result of the sampling structure (e.g., lost data), we indicate a censored y_i in `occuTTD` instead by setting $y_i = Tmax_i$ in the y matrix provided to `unmarkedFrameOccuTTD`. You can provide either a single value of $Tmax$ to the `surveyLength` argument of `unmarkedFrameOccuTTD`, or provide a matrix, potentially with a unique value of $Tmax$ for each value of y . Note that in the latter case the value of y that will be interpreted by `occuTTD` as a censored observation (i.e., $Tmax$) will differ between observations!

Occupancy and detection can be estimated with only a single survey per site, unlike a traditional occupancy model that requires at least two replicated surveys at at least some sites. However, `occuTTD` also supports multiple surveys per site using the model described in Garrard et al. (2013).

Furthermore, multi-season dynamic models are supported, using the same basic structure as for standard occupancy models (see [colex](#)).

When `linkPsi = "cloglog"`, the complimentary log-log link function is used for *psi* instead of the logit link. The cloglog link relates occupancy probability to the intensity parameter of an underlying Poisson process (Kery and Royle 2016). Thus, if abundance at a site is can be modeled as $N_i \text{Poisson}(\lambda_i)$, where $\log(\lambda_i) = \alpha + \beta * x$, then presence/absence data at the site can be modeled as $Z_i \text{Binomial}(\psi_i)$ where $\text{cloglog}(\psi_i) = \alpha + \beta * x$.

Value

unmarkedFitOccuTTD object describing model fit.

Author(s)

Ken Kellner <contact@kenkellner.com>

References

- Garrard, G.E., Bekessy, S.A., McCarthy, M.A. and Wintle, B.A. 2008. When have we looked hard enough? A novel method for setting minimum survey effort protocols for flora surveys. *Austral Ecology* 33: 986-998.
- Garrard, G.E., McCarthy, M.A., Williams, N.S., Bekessy, S.A. and Wintle, B.A. 2013. A general model of detectability using species traits. *Methods in Ecology and Evolution* 4: 45-52.
- Kery, Marc, and J. Andrew Royle. 2016. *Applied Hierarchical Modeling in Ecology*, Volume 1. Academic Press.

See Also

[unmarked](#), [unmarkedFrameOccuTTD](#)

Examples

```
## Not run:

### Single season model
N <- 500; J <- 1

#Simulate occupancy
scovs <- data.frame(elev=c(scale(runif(N, 0,100))),
                    forest=runif(N,0,1),
                    wind=runif(N,0,1))

beta_psi <- c(-0.69, 0.71, -0.5)
psi <- plogis(cbind(1, scovs$elev, scovs$forest) %*% beta_psi)
z <- rbinom(N, 1, psi)

#Simulate detection
Tmax <- 10 #Same survey length for all observations
beta_lam <- c(-2, -0.2, 0.7)
```

```

rate <- exp(cbind(1, scovs$elev, scovs$wind) %*% beta_lam)
ttd <- rexp(N, rate)
ttd[z==0] <- Tmax #Censor at unoccupied sites
ttd[ttd>Tmax] <- Tmax #Censor when ttd was greater than survey length

#Build unmarkedFrame
umf <- unmarkedFrameOccuTTD(y=ttd, surveyLength=Tmax, siteCovs=scovs)

#Fit model
fit <- occuTTD(psiformula=~elev+forest, detformula=~elev+wind, data=umf)

#Predict psi values
predict(fit, type='psi', newdata=data.frame(elev=0.5, forest=1))

#Predict lambda values
predict(fit, type='det', newdata=data.frame(elev=0.5, wind=0))

#Calculate p, probability species is detected at a site given it is present
#for a value of lambda. This is equivalent to eq 4 of Garrard et al. 2008
lam <- predict(fit, type='det', newdata=data.frame(elev=0.5, wind=0))$Predicted
pexp(Tmax, lam)

#Estimated p for all observations
head(getP(fit))

### Dynamic model

N <- 1000; J <- 2; T <- 2
scovs <- data.frame(elev=c(scale(runif(N, 0,100))),
                    forest=runif(N,0,1),
                    wind=runif(N,0,1))

beta_psi <- c(-0.69, 0.71, -0.5)
psi <- plogis(cbind(1, scovs$elev, scovs$forest) %*% beta_psi)
z <- matrix(NA, N, T)
z[,1] <- rbinom(N, 1, psi)

#Col/ext process
ysc <- data.frame(forest=rep(scovs$forest, each=T),
                  elev=rep(scovs$elev, each=T))
c_b0 <- -0.4; c_b1 <- 0.3
gam <- plogis(c_b0 + c_b1 * scovs$forest)
e_b0 <- -0.7; e_b1 <- 0.4
ext <- plogis(e_b0 + e_b1 * scovs$elev)

for (i in 1:N){
  for (t in 1:(T-1)){
    if(z[i,t]==1){
      #ext
      z[i,t+1] <- rbinom(1, 1, (1-ext[i]))
    } else {
      #col
      z[i,t+1] <- rbinom(1,1, gam[i])
    }
  }
}

```

```

    }
  }
}

#Simulate detection
ocovs <- data.frame(obs=rep(c('A','B'),N*T))
Tmax <- 10
beta_lam <- c(-2, -0.2, 0.7)
rate <- exp(cbind(1, scovs$elev, scovs$wind) %*% beta_lam)
#Add second observer at each site
rateB <- exp(cbind(1, scovs$elev, scovs$wind) %*% beta_lam - 0.5)
#Across seasons
rate2 <- as.numeric(t(cbind(rate, rateB, rate, rateB)))
ttd <- rexp(N*T*2, rate2)
ttd <- matrix(ttd, nrow=N, byrow=T)
ttd[ttd>Tmax] <- Tmax
ttd[z[,1]==0,1:2] <- Tmax
ttd[z[,2]==0,3:4] <- Tmax

umf <- unmarkedFrameOccuTTD(y = ttd, surveyLength = Tmax,
                           siteCovs = scovs, obsCovs=ocovs,
                           yearlySiteCovs=ysc, numPrimary=2)

dim(umf@y) #num sites, (num surveys x num primary periods)

fit <- occuTTD(psiformula=~elev+forest,detformula=~elev+wind+obs,
              gammaformula=~forest, epsilonformula=~elev,
              data=umf,se=T,engine="C")

truth <- c(beta_psi, c_b0, c_b1, e_b0, e_b1, beta_lam, -0.5)

#Compare to truth
cbind(coef(fit), truth)

## End(Not run)

```

ovendata

Removal data for the Ovenbird

Description

Removal sampling data collected for the Ovenbird (*Seiurus aurocapillus*).

Usage

```
data(ovendata)
```

Format

The format is: chr "ovendata.list" which consists of

data matrix of removal counts

covariates data frame of site-level covariates

Source

J.A. Royle (see reference below)

References

Royle, J. A. (2004). Generalized estimators of avian abundance from count survey data. *Animal Biodiversity and Conservation*, 27(1), 375-386.

Examples

```
data(ovendata)
str(ovendata.list)
ovenFrame <- unmarkedFrameMPois(ovendata.list$data,
siteCovs=as.data.frame(scale(ovendata.list$covariates[, -1])), type = "removal")
```

parboot

Parametric bootstrap method for fitted models inheriting class.

Description

Simulate datasets from a fitted model, refit the model, and generate a sampling distribution for a user-specified fit-statistic.

Arguments

object	a fitted model inheriting class "unmarkedFit"
statistic	a function returning a vector of fit-statistics. First argument must be the fitted model. Default is sum of squared residuals.
nsim	number of bootstrap replicates
report	print fit statistic every 'report' iterations during resampling
seed	set seed for reproducible bootstrap
parallel	logical (default = TRUE) indicating whether to compute bootstrap on multiple cores, if present. If TRUE, suppresses reporting of bootstrapped statistics. Defaults to serial calculation when nsim < 100.
ncores	integer (default = one less than number of available cores) number of cores to use when bootstrapping in parallel.
...	Additional arguments to be passed to statistic

Details

This function simulates datasets based upon a fitted model, refits the model, and evaluates a user-specified fit-statistic for each simulation. Comparing this sampling distribution to the observed statistic provides a means of evaluating goodness-of-fit or assessing uncertainty in a quantity of interest.

Value

An object of class `parboot` with three slots:

<code>call</code>	<code>parboot</code> call
<code>t0</code>	Numeric vector of statistics for original fitted model.
<code>t.star</code>	<code>nsim</code> by <code>length(t0)</code> matrix of statistics for each simulation fit.

Author(s)

Richard Chandler <rbchan@uga.edu> and Adam Smith

See Also

[ranef](#)

Examples

```
data(linetran)
(dbreaksLine <- c(0, 5, 10, 15, 20))
lengths <- linetran$Length

ltUMF <- with(linetran, {
  unmarkedFrameDS(y = cbind(dc1, dc2, dc3, dc4),
    siteCovs = data.frame(Length, area, habitat), dist.breaks = dbreaksLine,
    tlength = lengths*1000, survey = "line", unitsIn = "m")
})

# Fit a model
(fm <- distsamp(~area ~habitat, ltUMF))

# Function returning three fit-statistics.
fitstats <- function(fm) {
  observed <- getY(fm@data)
  expected <- fitted(fm)
  resids <- residuals(fm)
  sse <- sum(resids^2)
  chisq <- sum((observed - expected)^2 / expected)
  freeTuke <- sum((sqrt(observed) - sqrt(expected))^2)
  out <- c(SSE=sse, Chisq=chisq, freemanTukey=freeTuke)
  return(out)
}

(pb <- parboot(fm, fitstats, nsim=25, report=1))
```

```

plot(pb, main="")

# Finite-sample inference for a derived parameter.
# Population size in sampled area

Nhat <- function(fm) {
  sum(bup(ranef(fm, K=50)))
}

set.seed(345)
(pb.N <- parboot(fm, Nhat, nsim=25, report=5))

# Compare to empirical Bayes confidence intervals
colSums(confint(ranef(fm, K=50)))

```

pcount

*Fit the N-mixture model of Royle (2004)***Description**

Fit the N-mixture model of Royle (2004)

Usage

```

pcount(formula, data, K, mixture=c("P", "NB", "ZIP"),
       starts, method="BFGS", se=TRUE, engine=c("C", "R"), ...)

```

Arguments

formula	Double right-hand side formula describing covariates of detection and abundance, in that order
data	an unmarkedFramePCount object supplying data to the model.
K	Integer upper index of integration for N-mixture. This should be set high enough so that it does not affect the parameter estimates. Note that computation time will increase with K.
mixture	character specifying mixture: "P", "NB", or "ZIP".
starts	vector of starting values
method	Optimization method used by optim .
se	logical specifying whether or not to compute standard errors.
engine	Either "C" or "R" to use fast C++ code or native R code during the optimization.
...	Additional arguments to optim, such as lower and upper bounds

Details

This function fits N-mixture model of Royle (2004) to spatially replicated count data.

See [unmarkedFramePCount](#) for a description of how to format data for pcount.

This function fits the latent N-mixture model for point count data (Royle 2004, Kery et al 2005).

The latent abundance distribution, $f(N|\theta)$ can be set as a Poisson, negative binomial, or zero-inflated Poisson random variable, depending on the setting of the mixture argument, mixture = "P", mixture = "NB", mixture = "ZIP" respectively. For the first two distributions, the mean of N_i is λ_i . If $N_i \sim NB$, then an additional parameter, α , describes dispersion (lower α implies higher variance). For the ZIP distribution, the mean is $\lambda_i(1 - \psi)$, where psi is the zero-inflation parameter.

The detection process is modeled as binomial: $y_{ij} \sim \text{Binomial}(N_i, p_{ij})$.

Covariates of λ_i use the log link and covariates of p_{ij} use the logit link.

Value

unmarkedFit object describing the model fit.

Author(s)

Ian Fiske and Richard Chandler

References

Royle, J. A. (2004) N-Mixture Models for Estimating Population Size from Spatially Replicated Counts. *Biometrics* 60, pp. 108–105.

Kery, M., Royle, J. A., and Schmid, H. (2005) Modeling Avian Abundance from Replicated Counts Using Binomial Mixture Models. *Ecological Applications* 15(4), pp. 1450–1461.

Johnson, N.L, A.W. Kemp, and S. Kotz. (2005) Univariate Discrete Distributions, 3rd ed. Wiley.

See Also

[unmarkedFramePCount](#), [pcountOpen](#), [ranef](#), [parboot](#)

Examples

```
# Simulate data
set.seed(35)
nSites <- 100
nVisits <- 3
x <- rnorm(nSites)           # a covariate
beta0 <- 0
beta1 <- 1
lambda <- exp(beta0 + beta1*x) # expected counts at each site
N <- rpois(nSites, lambda)    # latent abundance
y <- matrix(NA, nSites, nVisits)
p <- c(0.3, 0.6, 0.8)        # detection prob for each visit
for(j in 1:nVisits) {
  y[,j] <- rbinom(nSites, N, p[j])
}
```

```

    }

# Organize data
visitMat <- matrix(as.character(1:nVisits), nSites, nVisits, byrow=TRUE)

umf <- unmarkedFramePCount(y=y, siteCovs=data.frame(x=x),
  obsCovs=list(visit=visitMat))
summary(umf)

# Fit a model
fm1 <- pcount(~visit-1 ~ x, umf, K=50)
fm1

plogis(coef(fm1, type="det")) # Should be close to p

# Empirical Bayes estimation of random effects
(fm1re <- ranef(fm1))
plot(fm1re, subset=site %in% 1:25, xlim=c(-1,40))
sum(bup(fm1re))          # Estimated population size
sum(N)                   # Actual population size

## Not run:

# Real data
data(mallard)
mallardUMF <- unmarkedFramePCount(mallard.y, siteCovs = mallard.site,
  obsCovs = mallard.obs)
(fm.mallard <- pcount(~ ivel+ date + I(date^2) ~ length + elev + forest, mallardUMF, K=30))
(fm.mallard.nb <- pcount(~ date + I(date^2) ~ length + elev, mixture = "NB", mallardUMF, K=30))

## End(Not run)

```

pcount.spHDS

Fit spatial hierarchical distance sampling model.

Description

Function fits an N-mixture model for a discrete state space with raster covariates, and a detection function which decreases with distance from the observer, assumed to be at the centre. See Kery & Royle (2016) Section 9.8.4 for details.

Usage

```

pcount.spHDS(formula, data, K, mixture = c("P", "NB", "ZIP"), starts,
  method = "BFGS", se = TRUE, ...)

```

Arguments

formula	Double right-hand side formula describing covariates of detection and abundance, in that order. Detection model should be specified without an intercept, for example: $\sim -1 + I(\text{dist}^2)$, where <i>dist</i> is a covariate giving the distance of each cell of the raster from the observer. Internally this forces the intercept $p(0) = 1$, conventional for distance sampling models (see Kery & Royle (2016) for explanation). More general models work but may not honor that constraint. e.g., $\sim 1, \sim \text{dist}, \sim I(\text{dist}^2), \sim \text{dist} + I(\text{dist}^2)$
data	an unmarkedFramePCount object supplying data to the model.
K	Integer upper index of integration for N-mixture. This should be set high enough so that it does not affect the parameter estimates. Note that computation time will increase with K.
mixture	character specifying mixture: Poisson (P), Negative-Binomial (NB), or Zero Inflated Poisson (ZIP).
starts	vector of starting values
method	Optimization method used by optim .
se	logical specifying whether or not to compute standard errors.
...	Additional arguments to <i>optim</i> , such as lower and upper bounds

Value

unmarkedFit object describing the model fit.

Author(s)

Kery & Royle

References

Kery & Royle (2016) *Applied Hierarchical Modeling in Ecology* Section 9.8.4

Examples

```
## Simulate some data to analyse
# This is based on Kery and Royle (2016) section 9.8.3
# See AHMbook::sim.spatialDS for more simulation options.

# We will simulate distance data for a logit detection function with sigma = 1,
# for a 6x6 square, divided into a 30 x 30 grid of pixels (900 in all), with the
# observer in the centre.

set.seed(2017)

## 1. Create coordinates for 30 x 30 grid
grx <- seq(0.1, 5.9, 0.2) # mid-point coordinates
gr <- expand.grid(grx, grx) # data frame with coordinates of pixel centres
```

```

## 2a. Simulate spatially correlated Habitat covariate
# Get the pair-wise distances between pixel centres
tmp <- as.matrix(dist(gr)) # a 900 x 900 matrix
# Correlation is a negative exponential function of distance, with scale parameter = 1
V <- exp(-tmp/1)
Habitat <- crossprod(t(chol(V)), rnorm(900))

## 2b. Do a detection covariate: the distance of each pixel centre from the observer
dist <- sqrt((gr[,1]-3)^2 + (gr[,2]-3)^2)

## 3. Simulate the true population
# Probability that an animal is in a pixel depends on the Habitat covariate, with
# coefficient beta:
beta <- 1
probs <- exp(beta*Habitat) / sum(exp(beta*Habitat))
# Allocate 600 animals to the 900 pixels, get the pixel ID for each animal
pixel.id <- sample(1:900, 600, replace=TRUE, prob=probs)

## 4. Simulate the detection process
# Get the distance of each animal from the observer
# (As an approximation, we'll treat animals as if they are at the pixel centre.)
d <- dist[pixel.id]
# Calculate probability of detection with logit detection function with
sigma <- 1
p <- 2*plogis(-d^2/(2*sigma^2))
# Simulate the 1/0 detection/nondetection vector
y <- rbinom(600, 1, p)
# Check the number of animals detected
sum(y)
# Select the pixel IDs for the animals detected and count the number in each pixel
detected.pixel.id <- pixel.id[y == 1]
pixel.count <- tabulate(detected.pixel.id, nbins=900)

## 5. Prepare the data for unmarked
# Centre the Habitat covariate
Habitat <- Habitat - mean(Habitat)
# Construct the unmarkedFramePCount object
umf <- unmarkedFramePCount(y=cbind(pixel.count), # y needs to be a 1-column matrix
  siteCovs=data.frame(dist=dist, Habitat=Habitat))
summary(umf)

## 6. Fit some models
(fm0 <- pcount.spHDS(~ -1 + I(dist^2) ~ 1, umf, K = 20))
(fm1 <- pcount.spHDS(~ -1 + I(dist^2) ~ Habitat, umf, K = 20))
# The true Habitat coefficient (beta above) = 1
# fm1 has much lower AIC; look at the population estimate
sum(predict(fm1, type="state"), 1)

```

Description

Fit the models of Dail and Madsen (2011) and Hostetler and Chandler (in press), which are generalized forms of the Royle (2004) N-mixture model for open populations.

Usage

```
pcountOpen(lambdaformula, gammaformula, omegaformula, pformula,
  data, mixture = c("P", "NB", "ZIP"), K, dynamics=c("constant", "autoreg",
  "notrend", "trend", "ricker", "gompertz"), fix=c("none", "gamma", "omega"),
  starts, method = "BFGS", se = TRUE, immigration = FALSE,
  iotaformula = ~1, ...)
```

Arguments

lambdaformula	Right-hand sided formula for initial abundance
gammaformula	Right-hand sided formula for recruitment rate (when dynamics is "constant", "autoreg", or "notrend") or population growth rate (when dynamics is "trend", "ricker", or "gompertz")
omegaformula	Right-hand sided formula for apparent survival probability (when dynamics is "constant", "autoreg", or "notrend") or equilibrium abundance (when dynamics is "ricker" or "gompertz")
pformula	Right-hand sided formula for detection probability
data	An object of class unmarkedFramePCO . See details
mixture	character specifying mixture: "P", "NB", or "ZIP" for the Poisson, negative binomial, and zero-inflated Poisson distributions.
K	Integer defining upper bound of discrete integration. This should be higher than the maximum observed count and high enough that it does not affect the parameter estimates. However, the higher the value the slower the computation.
dynamics	Character string describing the type of population dynamics. "constant" indicates that there is no relationship between omega and gamma. "autoreg" is an auto-regressive model in which recruitment is modeled as $\gamma N_{i,t-1}$. "notrend" model gamma as $\lambda(1-\omega)$ such that there is no temporal trend. "trend" is a model for exponential growth, $N_{i,t} = N_{i,t-1} \gamma$, where gamma in this case is finite rate of increase (normally referred to as lambda). "ricker" and "gompertz" are models for density-dependent population growth. "ricker" is the Ricker-logistic model, $N_{i,t} = N_{i,t-1} \exp(\gamma(1 - N_{i,t-1}/\omega))$, where gamma is the maximum instantaneous population growth rate (normally referred to as r) and omega is the equilibrium abundance (normally referred to as K). "gompertz" is a modified version of the Gompertz-logistic model, $N_{i,t} = N_{i,t-1} \exp(\gamma(1 - \log(N_{i,t-1} + 1)/\log(\omega + 1)))$, where the interpretations of gamma and omega are similar to in the Ricker model.
fix	If "omega", omega is fixed at 1. If "gamma", gamma is fixed at 0.
starts	vector of starting values
method	Optimization method used by optim .

se	logical specifying whether or not to compute standard errors.
immigration	logical specifying whether or not to include an immigration term (iota) in population dynamics.
iotaformula	Right-hand sided formula for average number of immigrants to a site per time step
...	additional arguments to be passed to optim .

Details

These models generalize the Royle (2004) N-mixture model by relaxing the closure assumption. The models include two or three additional parameters: gamma, either the recruitment rate (births and immigrations), the finite rate of increase, or the maximum instantaneous rate of increase; omega, either the apparent survival rate (deaths and emigrations) or the equilibrium abundance (carrying capacity); and iota, the number of immigrants per site and year. Estimates of population size at each time period can be derived from these parameters, and thus so can trend estimates. Or, trend can be estimated directly using `dynamics="trend"`.

When immigration is set to FALSE (the default), iota is not modeled. When immigration is set to TRUE and dynamics is set to "autoreg", the model will separately estimate birth rate (gamma) and number of immigrants (iota). When immigration is set to TRUE and dynamics is set to "trend", "ricker", or "gompertz", the model will separately estimate local contributions to population growth (gamma and omega) and number of immigrants (iota).

The latent abundance distribution, $f(N|\theta)$ can be set as a Poisson, negative binomial, or zero-inflated Poisson random variable, depending on the setting of the mixture argument, `mixture = "P"`, `mixture = "NB"`, `mixture = "ZIP"` respectively. For the first two distributions, the mean of N_i is λ_i . If $N_i \sim NB$, then an additional parameter, α , describes dispersion (lower α implies higher variance). For the ZIP distribution, the mean is $\lambda_i(1 - \psi)$, where ψ is the zero-inflation parameter.

For "constant", "autoreg", or "notrend" dynamics, the latent abundance state following the initial sampling period arises from a Markovian process in which survivors are modeled as $S_{it} \sim \text{Binomial}(N_{it-1}, \omega_{it})$, and recruits follow $G_{it} \sim \text{Poisson}(\gamma_{it})$. Alternative population dynamics can be specified using the dynamics and immigration arguments.

The detection process is modeled as binomial: $y_{ijt} \sim \text{Binomial}(N_{it}, p_{ijt})$.

λ_i , γ_{it} , and ω_{it} are modeled using the the log link. p_{ijt} is modeled using the logit link. ω_{it} is either modeled using the logit link (for "constant", "autoreg", or "notrend" dynamics) or the log link (for "ricker" or "gompertz" dynamics). For "trend" dynamics, ω_{it} is not modeled.

Value

An object of class `unmarkedFitPCO`.

Warning

This function can be extremely slow, especially if there are covariates of gamma or omega. Consider testing the timing on a small subset of the data, perhaps with `se=FALSE`. Finding the lowest value of K that does not affect estimates will also help with speed.

Note

When gamma or omega are modeled using year-specific covariates, the covariate data for the final year will be ignored; however, they must be supplied.

If the time gap between primary periods is not constant, an M by T matrix of integers should be supplied to [unmarkedFramePCO](#) using the primaryPeriod argument.

Secondary sampling periods are optional, but can greatly improve the precision of the estimates.

Author(s)

Richard Chandler <rbchan@uga.edu> and Jeff Hostetler

References

Royle, J. A. (2004) N-Mixture Models for Estimating Population Size from Spatially Replicated Counts. *Biometrics* 60, pp. 108–105.

Dail, D. and L. Madsen (2011) Models for Estimating Abundance from Repeated Counts of an Open Metapopulation. *Biometrics*. 67, pp 577-587.

Hostetler, J. A. and R. B. Chandler (2015) Improved State-space Models for Inference about Spatial and Temporal Variation in Abundance from Count Data. *Ecology* 96:1713-1723.

See Also

[pcount](#), [unmarkedFramePCO](#)

Examples

```
## Simulation
## No covariates, constant time intervals between primary periods, and
## no secondary sampling periods

set.seed(3)
M <- 50
T <- 5
lambda <- 4
gamma <- 1.5
omega <- 0.8
p <- 0.7
y <- N <- matrix(NA, M, T)
S <- G <- matrix(NA, M, T-1)
N[,1] <- rpois(M, lambda)
for(t in 1:(T-1)) {
  S[,t] <- rbinom(M, N[,t], omega)
  G[,t] <- rpois(M, gamma)
  N[,t+1] <- S[,t] + G[,t]
}
y[] <- rbinom(M*T, N, p)
```

```

# Prepare data
umf <- unmarkedFramePCO(y = y, numPrimary=T)
summary(umf)

# Fit model and backtransform
(m1 <- pcountOpen(~1, ~1, ~1, ~1, umf, K=20)) # Typically, K should be higher

(lam <- coef(backTransform(m1, "lambda")))) # or
lam <- exp(coef(m1, type="lambda"))
gam <- exp(coef(m1, type="gamma"))
om <- plogis(coef(m1, type="omega"))
p <- plogis(coef(m1, type="det"))

## Not run:
# Finite sample inference. Abundance at site i, year t
re <- ranef(m1)
devAskNewPage(TRUE)
plot(re, layout=c(5,5), subset = site %in% 1:25 & year %in% 1:2,
      xlim=c(-1,15))
devAskNewPage(FALSE)

(N.hat1 <- colSums(bup(re)))

# Expected values of N[i,t]
N.hat2 <- matrix(NA, M, T)
N.hat2[,1] <- lam
for(t in 2:T) {
  N.hat2[,t] <- om*N.hat2[,t-1] + gam
}

rbind(N=colSums(N), N.hat1=N.hat1, N.hat2=colSums(N.hat2))

## End(Not run)

```

piFuns

Compute multinomial cell probabilities

Description

Compute the cell probabilities used in the multinomial-Poisson models [multinomPois](#) and [gmult-mix](#). These functions use piFuns *internally* to calculate multinomial likelihoods from the occasion-wise detection probabilities. The only reason to call them directly is to check their behaviour.

Usage

```

removalPiFun(p)
doublePiFun(p)

```


Arguments

p matrix of detection probabilities at each site for each observation

Details

These two functions are provided as examples of possible functions to calculate multinomial cell probabilities. Users may write their own functions for specific sampling designs (see the example).

Value

For removalPiFun, a matrix of cell probabilities for each site and sampling period.

For doublePiFun, a matrix of cell probabilities for each site and observer combination. Column one is probability observer 1 but not observer 2 detects the object, column two is probability that observer 2 but not observer 1 detects the object, and column 3 is probability of both detecting.

See Also

[makePiFuns](#) for factory functions to create customised piFuns.

Examples

```
(pRem <- matrix(0.5, nrow=3, ncol=3)) # Capture probabilities
removalPiFun(pRem) # Cell probs

(pDouble <- matrix(0.5, 3, 2)) # Observer detection probs
doublePiFun(pDouble) # Cell probs

# A user-defined piFun calculating removal probs when time intervals differ.
# Here 10-minute counts were divided into 2, 3, and 5 minute intervals.
# This function could be supplied to unmarkedFrameMPois along with the obsToY
# argument shown below.

instRemPiFun <- function(p) {
  M <- nrow(p)
  J <- ncol(p)
  pi <- matrix(NA, M, J)
  p[,1] <- pi[,1] <- 1 - (1 - p[,1])^2
  p[,2] <- 1 - (1 - p[,2])^3
  p[,3] <- 1 - (1 - p[,3])^5
  for(i in 2:J) {
    pi[,i] <- pi[, i - 1]/p[, i - 1] * (1 - p[, i - 1]) * p[, i]
  }
  return(pi)
}

instRemPiFun(pRem)

# Associated obsToY matrix required by unmarkedFrameMPois
o2y <- diag(3) # if y has 3 columns
o2y[upper.tri(o2y)] <- 1
```

o2y

pointtran

*Simulated point-transect data***Description**

Response matrix of animals detected in five distance classes plus two covariates.

Usage

```
data(pointtran)
```

Format

A data frame with 30 observations on the following 7 variables.

dc1 Counts in distance class 1 [0-5 m)

dc2 Counts in distance class 2 [5-10 m)

dc3 Counts in distance class 3 [10-15 m)

dc4 Counts in distance class 4 [15-20 m)

dc5 Counts in distance class 5 [20-25 m)

area a numeric vector

habitat a factor with levels A B C

Examples

```
data(pointtran)
pointtran

# Format for distsamp()
ptUMF <- with(pointtran, {
  unmarkedFrameDS(y = cbind(dc1, dc2, dc3, dc4, dc5),
    siteCovs = data.frame(area, habitat),
    dist.breaks = seq(0, 25, by=5), survey = "point", unitsIn = "m")
})
```

posteriorSamples	<i>Draw samples from the posterior predictive distribution</i>
------------------	--

Description

Draw samples from the empirical Bayes posterior predictive distribution derived from unmarked models or ranef objects

Usage

```
## S4 method for signature 'unmarkedRanef'
posteriorSamples(object, nsims=100, ...)
## S4 method for signature 'unmarkedFit'
posteriorSamples(object, nsims=100, ...)
```

Arguments

object	An object inheriting class unmarkedRanef or unmarkedFit
nsims	Number of draws to make from the posterior predictive distribution
...	Other arguments

Value

unmarkedPostSamples object containing the draws from the posterior predictive distribution. The draws are in the @samples slot.

Author(s)

Ken Kellner <contact@kenkellner.com>

See Also

[ranef](#), [predict](#)

Examples

```
# Simulate data under N-mixture model
set.seed(4564)
R <- 20
J <- 5
N <- rpois(R, 10)
y <- matrix(NA, R, J)
y[] <- rbinom(R*J, N, 0.5)

# Fit model
umf <- unmarkedFramePCount(y=y)
fm <- pcount(~1 ~1, umf, K=50)
```

```
# Estimates of conditional abundance distribution at each site
(re <- ranef(fm))

#Draw from the posterior predictive distribution
(ppd <- posteriorSamples(re, nsims=100))
```

predict-methods

Methods for Function predict in Package 'unmarked'

Description

These methods return predicted values from fitted model objects.

Methods

```
signature(object = "unmarkedFit") "type" must be either 'state' or 'det'.
signature(object = "unmarkedFitColExt") "type" must be 'psi', 'col', 'ext', or 'det'.
signature(object = "unmarkedFitGMM") "type" must be 'lambda', 'psi', 'det'
signature(object = "unmarkedFitList") "type" depends upon the fitted models
signature(object = "unmarkedRanef") Use this method to generate the empirical Bayes posterior predictive distribution for functions of the random variables (latent abundance or occurrence).
```

In addition to the output object from `ranef`, you must also supply a custom function to argument `func`. The function must take as input a matrix with dimensions $M \times T$, where M is the number of sites and T is the number of primary periods ($T=1$ for single-season models). The output of this function should be a vector or matrix containing the derived parameters of interest.

You may also manually set the number of draws from the posterior predictive distribution with argument `nsims`; the default is 100.

The output of `predict` will be a vector or array with one more dimension than the output of the function supplied `func`, corresponding to the number of draws requested `nsims`. For example, if `func` outputs a scalar, the output of `predict` will be a vector with length equal to `nsims`. If `func` outputs a 3×2 matrix, the output of `predict` will be an array with dimensions $3 \times 2 \times nsims$. See [ranef](#) for an example.

Alternatively, you can use the [posteriorSamples](#) function on the `ranef` output object to obtain the full posterior predictive distribution. This is useful if you are having trouble designing your custom function or if you want to obtain multiple different derived parameters from the same posterior predictive distribution.

ranef-methods

Methods for Function ranef in Package **unmarked****Description**

Estimate posterior distributions of the random variables (latent abundance or occurrence) using empirical Bayes methods. These methods return an object storing the posterior distributions of the latent variables at each site, and for each year (primary period) in the case of open population models. See [unmarkedRanef-class](#) for methods used to manipulate the returned object.

Methods

signature(object = "unmarkedFitOccu") Computes the conditional distribution of occurrence given the data and the estimates of the fixed effects, $Pr(z_i = 1|y_{ij}, \hat{\psi}_i, \hat{p}_{ij})$

signature(object = "unmarkedFitOccuRN") Computes the conditional abundance distribution given the data and the estimates of the fixed effects, $Pr(N_i = k|y_{ij}, \hat{\psi}_i, \hat{r}_{ij})k = 0, 1, \dots, K$

signature(object = "unmarkedFitPCount") $Pr(N_i = k|y_{ij}, \hat{\lambda}_i, \hat{p}_{ij})k = 0, 1, \dots, K$

signature(object = "unmarkedFitMPois") $Pr(N_i = k|y_{ij}, \hat{\lambda}_i, \hat{p}_{ij})k = 0, 1, \dots, K$

signature(object = "unmarkedFitDS") $Pr(N_i = k|y_{i,1:J}, \hat{\lambda}_i, \hat{\sigma}_i)k = 0, 1, \dots, K$

signature(object = "unmarkedFitGMM") $Pr(M_i = k|y_{i,1:J,t}, \hat{\lambda}_i, \hat{\phi}_{it}, \hat{p}_{ijt})k = 0, 1, \dots, K$

signature(object = "unmarkedFitGDS") $Pr(M_i = k|y_{i,1:J,t}, \hat{\lambda}_i, \hat{\phi}_{it}, \hat{\sigma}_{it})k = 0, 1, \dots, K$

signature(object = "unmarkedFitColExt") $Pr(z_{it} = 1|y_{ijt}, \hat{\psi}_i, \hat{\gamma}_{it}, \hat{\epsilon}_{it}, \hat{p}_{ijt})$

signature(object = "unmarkedFitPCO") $Pr(N_{it} = k|y_{ijt}, \hat{\lambda}_i, \hat{\gamma}_{it}, \hat{\omega}_{it}, \hat{l}_{it}, \hat{p}_{ijt})k = 0, 1, \dots, K$

Warning

Empirical Bayes methods can underestimate the variance of the posterior distribution because they do not account for uncertainty in the hyperparameters (lambda or psi). Eventually, we hope to add methods to account for the uncertainty of the hyperparameters.

Note also that the posterior mode appears to exhibit some bias as an estimator of abundance. Consider using the posterior mean instead, even though it will not be an integer in general. More simulation studies are needed to evaluate the performance of empirical Bayes methods for these models.

Note

From Carlin and Louis (1996): "... the Bayesian approach to inference depends on a prior distribution for the model parameters. This prior can depend on unknown parameters which in turn may follow some second-stage prior. This sequence of parameters and priors constitutes a hierarchical model. The hierarchy must stop at some point, with all remaining prior parameters assumed known. Rather than make this assumption, the basic empirical Bayes approach uses the observed data to estimate these final stage parameters (or to estimate the Bayes rule), and proceeds as in a standard Bayesian analysis."

Author(s)

Richard Chandler <rbchan@uga.edu>

References

- Laird, N.M. and T.A. Louis. 1987. Empirical Bayes confidence intervals based on bootstrap samples. *Journal of the American Statistical Association* 82:739–750.
- Carlin, B.P and T.A Louis. 1996. *Bayes and Empirical Bayes Methods for Data Analysis*. Chapman and Hall/CRC.
- Royle, J.A and R.M. Dorazio. 2008. *Hierarchical Modeling and Inference in Ecology*. Academic Press.

See Also

[unmarkedRanef-class](#)

Examples

```
# Simulate data under N-mixture model
set.seed(4564)
R <- 20
J <- 5
N <- rpois(R, 10)
y <- matrix(NA, R, J)
y[] <- rbinom(R*J, N, 0.5)

# Fit model
umf <- unmarkedFramePCount(y=y)
fm <- pcount(~1 ~1, umf, K=50)

# Estimates of conditional abundance distribution at each site
(re <- ranef(fm))
# Best Unbiased Predictors
bup(re, stat="mean")      # Posterior mean
bup(re, stat="mode")     # Posterior mode
confint(re, level=0.9) # 90% CI

# Plots
plot(re, subset=site %in% c(1:10), layout=c(5, 2), xlim=c(-1,20))

# Compare estimates to truth
sum(N)
sum(bup(re))

# Extract all values in convenient formats
post.df <- as(re, "data.frame")
head(post.df)
post.arr <- as(re, "array")

#Generate posterior predictive distribution for a function
#of random variables using predict()
```

```

#First, create a function that operates on a vector of
#length M (if you fit a single-season model) or a matrix of
#dimensions MxT (if a dynamic model), where
#M = nsites and T = n primary periods
#Our function will generate mean abundance for sites 1-10 and sites 11-20
myfunc <- function(x){ #x will be length 20 since M=20

  #Mean of first 10 sites
  group1 <- mean(x[1:10])
  #Mean of sites 11-20
  group2 <- mean(x[11:20])

  #Naming elements of the output is optional but helpful
  return(c(group1=group1, group2=group2))

}

#Get 100 samples of the values calculated in your function
(pr <- predict(re, func=myfunc, nsims=100))

#Summarize posterior
data.frame(mean=rowMeans(pr),
           se=apply(pr, 1, stats::sd),
           lower=apply(pr, 1, stats::quantile, 0.025),
           upper=apply(pr, 1, stats::quantile, 0.975))

#Alternatively, you can return the posterior predictive distribution
#and run operations on it separately
(ppd <- posteriorSamples(re, nsims=100))

```

Description

Extract standard errors of parameter estimates from a fitted model.

Methods

obj = "linCombOrBackTrans" A model prediction

obj = "unmarkedEstimate" See [unmarkedEstimate-class](#)

obj = "unmarkedFit" A fitted model

sight2perpdist	<i>Convert sight distance and sight angle to perpendicular distance.</i>
----------------	--

Description

When distance data are collected on line transects using sight distances and sight angles, they need to be converted to perpendicular distances before analysis.

Usage

```
sight2perpdist(sightdist, sightangle)
```

Arguments

sightdist	Distance from observer
sightangle	Angle from center line. In degrees between 0 and 180.

Value

Perpendicular distance

See Also

[distsamp](#)

Examples

```
round(sight2perpdist(10, c(0, 45, 90, 135, 180)))
```

simulate-methods	<i>Methods for Function simulate in Package ‘unmarked’</i>
------------------	--

Description

Simulate data from a fitted model.

Usage

```
## S4 method for signature 'unmarkedFitColExt'
simulate(object, nsim, seed, na.rm)
## S4 method for signature 'unmarkedFitDS'
simulate(object, nsim, seed, na.rm)
## S4 method for signature 'unmarkedFitMPois'
simulate(object, nsim, seed, na.rm)
## S4 method for signature 'unmarkedFitOccu'
simulate(object, nsim, seed, na.rm)
```



```
## S4 method for signature 'unmarkedFitOccuRN'
simulate(object, nsim, seed, na.rm)
## S4 method for signature 'unmarkedFitPCount'
simulate(object, nsim, seed, na.rm)
```

Arguments

<code>object</code>	Fitted model of appropriate S4 class
<code>nsim</code>	Number of simulations
<code>seed</code>	Seed for random number generator. Not currently implemented
<code>na.rm</code>	Logical, should missing values be removed?

Methods

`object = "unmarkedFitColExt"` A model fit by [colext](#)

`object = "unmarkedFitDS"` A model fit by [distsamp](#)

`object = "unmarkedFitMPois"` A model fit by [multinomPois](#)

`object = "unmarkedFitOccu"` A model fit by [occu](#)

`object = "unmarkedFitOccuRN"` A model fit by [occuRN](#)

`object = "unmarkedFitPCount"` A model fit by [pcount](#)

SSE

Compute Sum of Squared Residuals for a Model Fit.

Description

Compute the sum of squared residuals for an unmarked fit object. This is useful for a [parboot](#).

Usage

```
SSE(fit, ...)
```

Arguments

<code>fit</code>	An unmarked fit object.
<code>...</code>	Additional arguments to be passed to statistic

Value

A numeric value for the models SSE.

See Also

[parboot](#)

Switzerland	<i>Swiss landscape data</i>
-------------	-----------------------------

Description

Spatially-referenced data on elevation, forest cover, and water at a 1km-sq resolution.

Usage

```
data(Switzerland)
```

Format

A data frame with 42275 observations on the following 5 variables.

x Easting (m)

y Northing (m)

elevation a numeric vector (m)

forest a numeric vector (percent cover)

water a numeric vector (percent cover)

Details

Forest and water coverage (in percent area) was computed using the 1992-97 landcover dataset of the Swiss Federal Statistical Office (<http://www.bfs.admin.ch>). Median elevation (in metres) was computed using a median aggregation of the digital elevation model of the Swiss Federal Statistical Office.

x and y are the coordinates of the center of each 1km² pixel.

The coordinate reference system intentionally not specified.

These data can only be used for non-profit projects. Otherwise, written permission must be obtained from the Swiss Federal Statistical Office

Source

Swiss Federal Statistical Office (<http://www.bfs.admin.ch>)

Examples

```
data(Switzerland)
str(Switzerland)
```

```
levelplot(elevation ~ x + y, Switzerland, aspect="iso",
  col.regions=terrain.colors(100))
```

```
## Not run:
library(raster)
```

```

el.r <- rasterFromXYZ(Switzerland[,c("x","y","elevation")], crs =
"+proj=somerc +lat_0=46.9524055555556 +lon_0=7.439583333333333
+k_0=1 +x_0=600000 +y_0=200000 +ellps=bessel
+towgs84=674.374,15.056,405.346,0,0,0,0 +units=m +no_defs")
plot(el.r)
spplot(el.r)

## End(Not run)

```

unmarkedEstimate-class

Class "unmarkedEstimate"

Description

Contains parameter estimates, covariance matrix, and metadata

Objects from the Class

Creating these objects is done internally not by users.

Slots

name: Object of class "character" storing parameter names
short.name: Object of class "character" storing abbreviated parameter names
estimates: Object of class "numeric"
covMat: Object of class "matrix"
covMatBS: Object of class "matrix"
invlink: Object of class "character"
invlinkGrad: Object of class "character"

Methods

backTransform signature(obj = "unmarkedEstimate")
coef signature(object = "unmarkedEstimate")
confint signature(object = "unmarkedEstimate")
linearComb signature(obj = "unmarkedEstimate", coefficients = "matrixOrVector")
SE signature(obj = "unmarkedEstimate")
show signature(object = "unmarkedEstimate")
vcov signature(object = "unmarkedEstimate")

Note

These methods are typically called within a call to a method for [unmarkedFit-class](#)

Examples

```
showClass("unmarkedEstimate")
```

```
unmarkedEstimateList-class
      Class "unmarkedEstimateList"
```

Description

Class to hold multiple unmarkedEstimates in an [unmarkedFit](#)

Slots

estimates: A "list" of models.

```
unmarkedFit-class      Class "unmarkedFit"
```

Description

Contains fitted model information which can be manipulated or extracted using the methods described below.

Slots

fitType: Object of class "character"
 call: Object of class "call"
 formula: Object of class "formula"
 data: Object of class "unmarkedFrame"
 sitesRemoved: Object of class "numeric"
 estimates: Object of class "unmarkedEstimateList"
 AIC: Object of class "numeric"
 opt: Object of class "list" containing results from [optim](#)
 negLogLike: Object of class "numeric"
 nllFun: Object of class "function"
 knownOcc: unmarkedFitOccu only: sites known to be occupied
 K: unmarkedFitPCount only: upper bound used in integration
 mixture: unmarkedFitPCount only: Mixing distribution
 keyfun: unmarkedFitDS only: detection function used by [distsamp](#)
 unitsOut: unmarkedFitDS only: density units

Methods

[signature(x = "unmarkedFit", i = "ANY", j = "ANY", drop = "ANY"): extract one of names(obj), eg 'state' or 'det'

backTransform signature(obj = "unmarkedFit"): back-transform parameters to original scale when no covariate effects are modeled

coef signature(object = "unmarkedFit"): returns parameter estimates. type can be one of names(obj), eg 'state' or 'det'. If altNames=TRUE estimate names are more specific.

confint signature(object = "unmarkedFit"): Returns confidence intervals. Must specify type and method (either "normal" or "profile")

fitted signature(object = "unmarkedFit"): returns expected values of Y

getData signature(object = "unmarkedFit"): extracts data

getP signature(object = "unmarkedFit"): calculates and extracts expected detection probabilities

getFP signature(object = "unmarkedFit"): calculates and extracts expected false positive detection probabilities

getB signature(object = "unmarkedFit"): calculates and extracts expected probabilities a true positive detection was classified as certain

hessian signature(object = "unmarkedFit"): Returns hessian matrix

linearComb signature(obj = "unmarkedFit", coefficients = "matrixOrVector"): Returns estimate and SE on original scale when covariates are present

mle signature(object = "unmarkedFit"): Same as coef(fit)?

names signature(x = "unmarkedFit"): Names of parameter levels

nllFun signature(object = "unmarkedFit"): returns negative log-likelihood used to estimate parameters

parboot signature(object = "unmarkedFit"): Parametric bootstrapping method to assess goodness-of-fit

plot signature(x = "unmarkedFit", y = "missing"): Plots expected vs. observed values

predict signature(object = "unmarkedFit"): Returns predictions and standard errors for original data or for covariates in a new data.frame

profile signature(fitted = "unmarkedFit"): used by confint method='profile'

residuals signature(object = "unmarkedFit"): returns residuals

sampleSize signature(object = "unmarkedFit"): returns number of sites in sample

SE signature(obj = "unmarkedFit"): returns standard errors

show signature(object = "unmarkedFit"): concise results

summary signature(object = "unmarkedFit"): results with more details

update signature(object = "unmarkedFit"): refit model with changes to one or more arguments

vcov signature(object = "unmarkedFit"): returns variance-covariance matrix

smoothed signature(object="unmarkedFitColExt"): Returns the smoothed trajectory from a colonization-extinction model fit. Takes additional logical argument mean which specifies whether or not to return the average over sites.

projected signature(object="unmarkedFitColExt"): Returns the projected trajectory from a colonization-extinction model fit. Takes additional logical argument mean which specifies whether or not to return the average over sites.

logLik signature(object="unmarkedFit"): Returns the log-likelihood.

LRT signature(m1="unmarkedFit", m2="unmarkedFit"): Returns the chi-squared statistic, degrees-of-freedom, and p-value from a Likelihood Ratio Test.

Note

This is a superclass with child classes for each fit type

Examples

```
showClass("unmarkedFit")

# Format removal data for multinomPois
data(ovendata)
ovenFrame <- unmarkedFrameMPois(y = ovendata.list$data,
siteCovs = as.data.frame(scale(ovendata.list$covariates[, -1])),
type = "removal")

# Fit a couple of models
(fm1 <- multinomPois(~ 1 ~ ufc + trba, ovenFrame))
summary(fm1)

# Apply a bunch of methods to the fitted model

# Look at the different parameter types
names(fm1)
fm1['state']
fm1['det']

# Coefficients from abundance part of the model
coef(fm1, type='state')

# Variance-covariance matrix
vcov(fm1, type='state')

# Confidence intervals using profiled likelihood
confint(fm1, type='state', method='profile')

# Expected values
fitted(fm1)

# Original data
getData(fm1)

# Detection probabilities
getP(fm1)

# log-likelihood
logLik(fm1)
```

```

# Back-transform detection probability to original scale
# backTransform only works on models with no covariates or
#   in conjunction with linearComb (next example)
backTransform(fm1, type = 'det')

# Predicted abundance at specified covariate values
(lc <- linearComb(fm1, c(Int = 1, ufc = 0, trba = 0), type='state'))
backTransform(lc)

# Assess goodness-of-fit
parboot(fm1)
plot(fm1)

# Predict abundance at specified covariate values.
newdat <- data.frame(ufc = 0, trba = seq(-1, 1, length=10))
predict(fm1, type='state', newdata=newdat)

# Number of sites in the sample
sampleSize(fm1)

# Fit a new model without covariates
(fmNull <- update(fm1, formula = ~1 ~1))

# Likelihood ratio test
LRT(fm1, fmNull)

```

unmarkedFitList-class *Class "unmarkedFitList"*

Description

Class to hold multiple fitted models from one of unmarked's fitting functions

Objects from the Class

Objects can be created by using the `fitList` function.

Slots

fits: A "list" of models.

Methods

coef signature(object = "unmarkedFitList"): Extract coefficients
SE signature(object = "unmarkedFitList"): Extract standard errors
modSel signature(object = "unmarkedFitList"): Model selection
predict signature(object = "unmarkedFitList"): Model-averaged prediction

Note

Model-averaging regression coefficients is intentionally not implemented.

See Also

[fitList](#), [unmarkedFit](#)

Examples

```
showClass("unmarkedFitList")

data(linetran)
(dbreaksLine <- c(0, 5, 10, 15, 20))
lengths <- linetran$Length * 1000

ltUMF <- with(linetran, {
  unmarkedFrameDS(y = cbind(dc1, dc2, dc3, dc4),
    siteCovs = data.frame(Length, area, habitat), dist.breaks = dbreaksLine,
    tlength = lengths, survey = "line", unitsIn = "m")
})

fm1 <- distsamp(~ 1 ~1, ltUMF)
fm2 <- distsamp(~ area ~1, ltUMF)
fm3 <- distsamp(~ 1 ~area, ltUMF)

f1 <- fitList(Null=fm1, A.=fm2, .A=fm3)
f1

coef(f1)
SE(f1)

ms <- modSel(f1, nullmod="Null")
ms
```

unmarkedFrame

Create an unmarkedFrame, or one of its child classes.

Description

Constructor for unmarkedFrames.

Usage

```
unmarkedFrame(y, siteCovs=NULL, obsCovs=NULL, mapInfo, obsToY)
```


Arguments

<code>y</code>	An $M \times J$ matrix of the observed measured data, where M is the number of sites and J is the maximum number of observations per site.
<code>siteCovs</code>	A data.frame of covariates that vary at the site level. This should have M rows and one column per covariate
<code>obsCovs</code>	Either a named list of data.frames of covariates that vary within sites, or a data.frame with $M \times J$ rows in site-major order.
<code>obsToY</code>	optional matrix specifying relationship between observation-level covariates and response matrix
<code>mapInfo</code>	geographic coordinate information. Currently ignored.

Details

`unmarkedFrame` is the S4 class that holds data structures to be passed to the model-fitting functions in `unmarked`.

An `unmarkedFrame` contains the observations (`y`), covariates measured at the observation level (`obsCovs`), and covariates measured at the site level (`siteCovs`). For a data set with M sites and J observations at each site, `y` is an $M \times J$ matrix. `obsCovs` and `siteCovs` are both data frames (see [data.frame](#)). `siteCovs` has M rows so that each row contains the covariates for the corresponding sites. `obsCovs` has $M \times \text{obsNum}$ rows so that each covariates is ordered by site first, then observation number. Missing values are coded with NA in any of `y`, `siteCovs`, or `obsCovs`.

Additionally, `unmarkedFrames` contain metadata: `obsToY`, `mapInfo`. `obsToY` is a matrix describing relationship between response matrix and observation-level covariates. Generally this does not need to be supplied by the user; however, it may be needed when using [multinomPois](#). For example, double observer sampling, `y` has 3 columns corresponding the observer 1, observer 2, and both, but there were only two independent observations. In this situation, `y` has 3 columns, but `obsToY` must be specified.

Several child classes of `unmarkedFrame` require additional metadata. For example, `unmarkedFrameDS` is used to organize distance sampling data for the [distsamp](#) function, and it has arguments `dist.breaks`, `tlength`, `survey`, and `unitsIn`, which specify the distance interval cut points, transect lengths, "line" or "point" transect, and units of measure, respectively.

All site-level covariates are automatically copied to `obsCovs` so that site level covariates are available at the observation level.

Value

an `unmarkedFrame` object

See Also

[unmarkedFrame-class](#), [unmarkedFrameOccu](#), [unmarkedFramePCount](#), [unmarkedFrameDS](#)

Examples

```
# Set up data for pcount()
```

```

data(mallard)
mallardUMF <- unmarkedFramePCount(mallard.y, siteCovs = mallard.site,
obsCovs = mallard.obs)
summary(mallardUMF)

# Set up data for occu()
data(frogs)
pferUMF <- unmarkedFrameOccu(pfer.bin)

# Set up data for distsamp()
data(linetran)
ltUMF <- with(linetran, {
  unmarkedFrameDS(y = cbind(dc1, dc2, dc3, dc4),
  siteCovs = data.frame(Length, area, habitat),
  dist.breaks = c(0, 5, 10, 15, 20),
  tlength = linetran$Length * 1000, survey = "line", unitsIn = "m")
})
summary(ltUMF)

# Set up data for multinomPois()
data(ovendata)
ovenFrame <- unmarkedFrameMPois(ovendata.list$data,
siteCovs=as.data.frame(scale(ovendata.list$covariates[, -1])),
type = "removal")
summary(ovenFrame)

## Not run:
# Set up data for colext()
frogUMF <- formatMult(masspcru)
summary(frogUMF)

## End(Not run)

```

unmarkedFrame-class *Class "unmarkedFrame"*

Description

Methods for manipulating, summarizing and viewing unmarkedFrames

Objects from the Class

Objects can be created by calls to the constructor function `unmarkedFrame`. These objects are passed to the data argument of the fitting functions.

Slots

y: Object of class "matrix"
obsCovs: Object of class "optionalDataFrame"
siteCovs: Object of class "optionalDataFrame"
mapInfo: Object of class "optionalMapInfo"
obsToY: Object of class "optionalMatrix"

Methods

[signature(x = "unmarkedFrame", i = "numeric", j = "missing", drop = "missing"): ...
[signature(x = "unmarkedFrame", i = "numeric", j = "numeric", drop = "missing"): ...
[signature(x = "unmarkedFrame", i = "missing", j = "numeric", drop = "missing"): ...
coordinates signature(object = "unmarkedFrame"): extract coordinates
getY signature(object = "unmarkedFrame"): extract y matrix
numSites signature(object = "unmarkedFrame"): extract M
numY signature(object = "unmarkedFrame"): extract ncol(y)
obsCovs signature(object = "unmarkedFrame"): extract observation-level covariates
obsCovs<- signature(object = "unmarkedFrame"): add or modify observation-level covariates
obsNum signature(object = "unmarkedFrame"): extract number of observations
obsToY signature(object = "unmarkedFrame"): ...
obsToY<- signature(object = "unmarkedFrame"): ...
plot signature(x = "unmarkedFrame", y = "missing"): visualize response variable. Takes additional argument panels which specifies how many panels data should be split over.
projection signature(object = "unmarkedFrame"): extract projection information
show signature(object = "unmarkedFrame"): view data as data.frame
siteCovs signature(object = "unmarkedFrame"): extract site-level covariates
siteCovs<- signature(object = "unmarkedFrame"): add or modify site-level covariates
summary signature(object = "unmarkedFrame"): summarize data

Note

This is a superclass with child classes for each fitting function

See Also

[unmarkedFrame](#), [unmarkedFit](#), [unmarked-package](#)

Examples

```
# Organize data for pcount()
data(mallard)
mallardUMF <- unmarkedFramePCount(mallard.y, siteCovs = mallard.site,
obsCovs = mallard.obs)

# Vizualize it
plot(mallardUMF)

mallardUMF

# Summarize it
summary(mallardUMF)

str(mallardUMF)

numSites(mallardUMF)

numY(mallardUMF)

obsNum(mallardUMF)

# Extract components of data
getY(mallardUMF)

obsCovs(mallardUMF)
obsCovs(mallardUMF, matrices = TRUE)

siteCovs(mallardUMF)

mallardUMF[1:5,] # First 5 rows in wide format

mallardUMF[,1:2] # First 2 observations
```

unmarkedFrameDS

*Organize data for the distance sampling model of Royle et al. (2004)
fit by `distsamp`*

Description

Organizes count data along with the covariates and metadata. This S4 class is required by the data argument of [distsamp](#)

Usage

```
unmarkedFrameDS(y, siteCovs=NULL, dist.breaks, tlength, survey,
  unitsIn, mapInfo)
```

Arguments

<code>y</code>	An RxJ matrix of count data, where R is the number of sites (transects) and J is the number of distance classes.
<code>siteCovs</code>	A data.frame of covariates that vary at the site level. This should have R rows and one column per covariate
<code>dist.breaks</code>	vector of distance cut-points delimiting the distance classes. It must be of length J+1.
<code>tlength</code>	A vector of length R containing the trasect lengths. This is ignored when survey="point".
<code>survey</code>	Either "point" or "line" for point- and line-transects.
<code>unitsIn</code>	Either "m" or "km" defining the measurement units for <i>both</i> <code>dist.breaks</code> and <code>tlength</code> .
<code>mapInfo</code>	Currently ignored

Details

unmarkedFrameDS is the S4 class that holds data to be passed to the [distsamp](#) model-fitting function.

Value

an object of class unmarkedFrameDS

Note

If you have continuous distance data, they must be "binned" into discrete distance classes, which are delimited by `dist.breaks`.

References

Royle, J. A., D. K. Dawson, and S. Bates (2004) Modeling abundance effects in distance sampling. *Ecology* 85, pp. 1591-1597.

See Also

[unmarkedFrame-class](#), [unmarkedFrame](#), [distsamp](#)

Examples

```
# Fake data
R <- 4 # number of sites
J <- 3 # number of distance classes

db <- c(0, 10, 20, 30) # distance break points

y <- matrix(c(
  5,4,3, # 5 detections in 0-10 distance class at this transect
  0,0,0,
  2,1,1,
  1,1,0), nrow=R, ncol=J, byrow=TRUE)
y

site.covs <- data.frame(x1=1:4, x2=factor(c('A','B','A','B')))
site.covs

umf <- unmarkedFrameDS(y=y, siteCovs=site.covs, dist.breaks=db, survey="point",
  unitsIn="m") # organize data
umf           # look at data
summary(umf)  # summarize
fm <- distsamp(~1 ~1, umf) # fit a model
```

unmarkedFrameDSO	<i>Create an object of class unmarkedFrameDSO that contains data used by distsampOpen.</i>
------------------	--

Description

Organizes distance sampling data and experimental design information from multiple primary periods along with associated covariates. This S4 class is required by the data argument of [distsampOpen](#)

Usage

```
unmarkedFrameDSO(y, siteCovs=NULL, yearlySiteCovs=NULL, numPrimary,
  primaryPeriod, dist.breaks, tlength, survey, unitsIn)
```

Arguments

y	An MxJT matrix of the repeated count data, where M is the number of sites (i.e., points or transects), J is the number of distance classes and T is the maximum number of primary sampling periods per site
siteCovs	A data.frame of covariates that vary at the site level. This should have M rows and one column per covariate

yearlySiteCovs	Either a named list of MxT data.frames , or a site-major data.frame with MT rows and 1 column per covariate
numPrimary	Maximum number of observed primary periods for each site
primaryPeriod	An MxJT matrix of integers indicating the primary period of each observation
dist.breaks	vector of distance cut-points delimiting the distance classes. It must be of length J+1
tlength	A vector of length R containing the transect lengths. This is ignored when survey="point"
survey	Either "point" or "line" for point- and line-transects
unitsIn	Either "m" or "km" defining the measurement units for <i>both</i> dist.breaks and tlength

Details

unmarkedFrameDSO is the S4 class that holds data to be passed to the [distsampOpen](#) model-fitting function. Unlike most unmarked functions, obsCovs cannot be supplied.

If you have continuous distance data, they must be "binned" into discrete distance classes, which are delimited by dist.breaks.

When gamma or omega are modeled using year-specific covariates, the covariate data for the final year will be ignored; however, they must be supplied.

If the time gap between primary periods is not constant, an M by T matrix of integers should be supplied using the primaryPeriod argument.

Value

an object of class unmarkedFrameDSO

See Also

[unmarkedFrame-class](#), [unmarkedFrame](#), [distsampOpen](#)

Examples

```
# Fake data
M <- 4 # number of sites
J <- 3 # number of distance classes
T <- 2 # number of primary periods

db <- c(0, 10, 20, 30) # distance break points

y <- matrix(c(
  5,4,3, 6,2,1, # In bin 1: 5 detections in primary period 1, 6 in period 2
  0,0,0, 0,1,0,
  2,1,1, 0,0,0,
  1,1,0, 1,1,1), nrow=M, ncol=J*T, byrow=TRUE)
y
```

```

# Primary periods of observations
# In this case there are no gaps
primPer <- matrix(as.integer(c(
  1,2,
  1,2,
  1,2,
  1,2)), nrow=M, ncol=T, byrow=TRUE)

#Site covs: M rows and 1 column per covariate
site.covs <- data.frame(x1=1:4, x2=factor(c('A','B','A','B')))
site.covs

#Yearly site covs on gamma/omega
ysc <- list(
  x3 = matrix(c(
    1,2,
    1,2,
    1,2,
    1,2), nrow=M, ncol=T, byrow=TRUE))

umf <- unmarkedFrameDSO(y=y, siteCovs=site.covs, yearlySiteCovs=ysc,
  numPrimary=T, primaryPeriod=primPer,
  dist.breaks=db, survey="point", unitsIn="m")

umf          # look at data
summary(umf) # summarize

```

unmarkedFrameMMO	<i>Create an object of class unmarkedFrameMMO that contains data used by <code>multmixOpen</code>.</i>
------------------	--

Description

Organizes count data and experimental design information from multiple primary periods along with associated covariates. This S4 class is required by the data argument of [multmixOpen](#)

Usage

```
unmarkedFrameMMO(y, siteCovs=NULL, obsCovs=NULL, yearlySiteCovs=NULL,
  numPrimary, type, primaryPeriod)
```

Arguments

y	An MxJT matrix of the repeated count data, where M is the number of sites (i.e., points or transects), J is the number of distance classes and T is the maximum number of primary sampling periods per site
siteCovs	A data.frame of covariates that vary at the site level. This should have M rows and one column per covariate

obsCovs	Either a named list of data.frames of covariates that vary within sites, or a data.frame with MxJT rows in site-major order.
yearlySiteCovs	Either a named list of MxT data.frames , or a site-major data.frame with MT rows and 1 column per covariate
numPrimary	Maximum number of observed primary periods for each site
type	Either "removal" for removal sampling, "double" for standard double observer sampling, or "depDouble" for dependent double observer sampling
primaryPeriod	An MxJT matrix of integers indicating the primary period of each observation

Details

unmarkedFrameMMO is the S4 class that holds data to be passed to the [multmixOpen](#) model-fitting function.

Options for the detection process (type) include equal-interval removal sampling ("removal"), double observer sampling ("double"), or dependent double-observer sampling ("depDouble"). Note that unlike the related functions [multinomPois](#) and [gmultmix](#), custom functions for the detection process (i.e., piFuns) are not supported. To request additional options contact the author.

When gamma or omega are modeled using year-specific covariates, the covariate data for the final year will be ignored; however, they must be supplied.

If the time gap between primary periods is not constant, an M by T matrix of integers should be supplied using the primaryPeriod argument.

Value

an object of class unmarkedFrameMMO

See Also

[unmarkedFrame-class](#), [unmarkedFrame](#), [multmixOpen](#)

Examples

```
#Generate some data
set.seed(123)
lambda=4; gamma=0.5; omega=0.8; p=0.5
M <- 100; T <- 5
y <- array(NA, c(M, 3, T))
N <- matrix(NA, M, T)
S <- G <- matrix(NA, M, T-1)

for(i in 1:M) {
  N[i,1] <- rpois(1, lambda)
  y[i,1,1] <- rbinom(1, N[i,1], p) # Observe some
  Nleft1 <- N[i,1] - y[i,1,1]     # Remove them
  y[i,2,1] <- rbinom(1, Nleft1, p) # ...
  Nleft2 <- Nleft1 - y[i,2,1]
  y[i,3,1] <- rbinom(1, Nleft2, p)
```

```

for(t in 1:(T-1)) {
  S[i,t] <- rbinom(1, N[i,t], omega)
  G[i,t] <- rpois(1, gamma)
  N[i,t+1] <- S[i,t] + G[i,t]
  y[i,1,t+1] <- rbinom(1, N[i,t+1], p)    # Observe some
  Nleft1 <- N[i,t+1] - y[i,1,t+1]        # Remove them
  y[i,2,t+1] <- rbinom(1, Nleft1, p)    # ...
  Nleft2 <- Nleft1 - y[i,2,t+1]
  y[i,3,t+1] <- rbinom(1, Nleft2, p)
}
}
y=matrix(y, M)

#Create some random covariate data
sc <- data.frame(x1=rnorm(100))

#Create unmarked frame
umf <- unmarkedFrameMMO(y=y, numPrimary=5, siteCovs=sc, type="removal")

summary(umf)

```

unmarkedFrameMPois	<i>Organize data for the multinomial-Poisson mixture model of Royle (2004) fit by multinomPois</i>
--------------------	--

Description

Organizes count data along with the covariates. This S4 class is required by the data argument of [multinomPois](#)

Usage

```
unmarkedFrameMPois(y, siteCovs=NULL, obsCovs=NULL, type, obsToY,
  mapInfo, piFun)
```

Arguments

y	An RxJ matrix of count data, where R is the number of sites (transects) and J is the maximum number of observations per site.
siteCovs	A data.frame of covariates that vary at the site level. This should have R rows and one column per covariate
obsCovs	Either a named list of RxJ data.frames or a data.frame with RxJ rows and one column per covariate. For the latter format, the covariates should be in site-major order.
type	Either "removal" for removal sampling, "double" for standard double observer sampling, or "depDouble" for dependent double observer sampling. If this argument not specified, the user must provide an obsToY matrix. See details.

obsToY	A matrix describing the relationship between obsCovs and y. This is necessary because under some sampling designs the dimensions of y do not equal the dimensions of each observation level covariate. For example, in double observer sampling there are 3 observations (seen only by observer A, detected only by observer B, and detected by both), but each observation-level covariate can only have 2 columns, one for each observer. This matrix is created automatically if type is specified.
mapInfo	Currently ignored
piFun	Function used to compute the multinomial cell probabilities from a matrix of detection probabilities. This is created automatically if type is specified.

Details

unmarkedFrameMPois is the S4 class that holds data to be passed to the [multinomPois](#) model-fitting function.

Value

an object of class unmarkedFrameMPois

References

Royle, J. A. (2004). Generalized estimators of avian abundance from count survey data. *Animal Biodiversity and Conservation*, 27(1), 375-386.

See Also

[unmarkedFrame-class](#), [unmarkedFrame](#), [multinomPois](#), [piFuns](#)

Examples

```
# Fake double observer data
R <- 4 # number of sites
J <- 2 # number of observers

y <- matrix(c(
  1,0,3,
  0,0,0,
  2,0,1,
  0,0,2), nrow=R, ncol=J+1, byrow=TRUE)
y

site.covs <- data.frame(x1=1:4, x2=factor(c('A','B','A','B')))
site.covs

obs.covs <- list(
  x3 = matrix(c(
    -1,0,
    -2,0,
    -3,1,
```

```

      0,0),
      nrow=R, ncol=J, byrow=TRUE),
x4 = matrix(c(
  'a','b',
  'a','b',
  'a','b',
  'a','b'),
  nrow=R, ncol=J, byrow=TRUE))
obs.covs

# Create unmarkedFrame
umf <- unmarkedFrameMPois(y=y, siteCovs=site.covs, obsCovs=obs.covs,
  type="double")

# The above is the same as:
o2y <- matrix(1, 2, 3)
pifun <- function(p)
{
  M <- nrow(p)
  pi <- matrix(NA, M, 3)
  pi[, 1] <- p[, 1] * (1 - p[, 2])
  pi[, 2] <- p[, 2] * (1 - p[, 1])
  pi[, 3] <- p[, 1] * p[, 2]
  return(pi)
}

umf <- unmarkedFrameMPois(y=y, siteCovs=site.covs, obsCovs=obs.covs,
  obsToY=o2y, piFun="pifun")

# Fit a model
fm <- multinomPois(~1 ~1, umf)

```

unmarkedFrameOccu	<i>Organize data for the single season occupancy models fit by occu and occuRN</i>
-------------------	--

Description

Organizes detection, non-detection data along with the covariates. This S4 class is required by the data argument of [occu](#) and [occuRN](#)

Usage

```
unmarkedFrameOccu(y, siteCovs=NULL, obsCovs=NULL, mapInfo)
```

Arguments

<code>y</code>	An RxJ matrix of the detection, non-detection data, where R is the number of sites, J is the maximum number of sampling periods per site.
<code>siteCovs</code>	A data.frame of covariates that vary at the site level. This should have M rows and one column per covariate
<code>obsCovs</code>	Either a named list of data.frames of covariates that vary within sites, or a data.frame with RxJ rows in site-major order.
<code>mapInfo</code>	Currently ignored

Details

unmarkedFrameOccu is the S4 class that holds data to be passed to the [occu](#) and [occuRN](#) model-fitting function.

Value

an object of class unmarkedFrameOccu

See Also

[unmarkedFrame-class](#), [unmarkedFrame](#), [occu](#), [occuRN](#)

Examples

```
# Fake data
R <- 4 # number of sites
J <- 3 # number of visits
y <- matrix(c(
  1,1,0,
  0,0,0,
  1,1,1,
  1,0,1), nrow=R, ncol=J, byrow=TRUE)
y

site.covs <- data.frame(x1=1:4, x2=factor(c('A','B','A','B')))
site.covs

obs.covs <- list(
  x3 = matrix(c(
    -1,0,1,
    -2,0,0,
    -3,1,0,
    0,0,0), nrow=R, ncol=J, byrow=TRUE),
  x4 = matrix(c(
    'a','b','c',
    'd','b','a',
    'a','a','c',
    'a','b','a'), nrow=R, ncol=J, byrow=TRUE))
obs.covs
```

```
umf <- unmarkedFrameOccu(y=y, siteCovs=site.covs,
  obsCovs=obs.covs) # organize data
umf           # look at data
summary(umf)   # summarize
fm <- occu(~1 ~1, umf) # fit a model
```

unmarkedFrameOccuFP	<i>Organize data for the single season occupancy models fit by occuFP</i>
---------------------	---

Description

Organizes detection, non-detection data along with the covariates. This S4 class is required by the data argument of [occu](#) and [occuRN](#)

Usage

```
unmarkedFrameOccuFP(y, siteCovs=NULL, obsCovs=NULL, type, mapInfo)
```

Arguments

y	An RxJ matrix of the detection, non-detection data, where R is the number of sites, J is the maximum number of sampling periods per site.
siteCovs	A data.frame of covariates that vary at the site level. This should have M rows and one column per covariate
obsCovs	Either a named list of data.frames of covariates that vary within sites, or a data.frame with RxJ rows in site-major order.
type	A vector with 3 values designating the number of occasions where data is of type 1, type 2, and type 3 - see occuFP for more details about data types.
mapInfo	Currently ignored

Details

unmarkedFrameOccuFP is the S4 class that holds data to be passed to the [occu](#) and [occuRN](#) model-fitting function.

Value

an object of class unmarkedFrameOccuFP

See Also

[unmarkedFrame-class](#), [unmarkedFrame](#), [occuFP](#)

Examples

```

n = 100
o = 10
o1 = 5
y = matrix(0,n,o)
p = .7
r = .5
fp = 0.05
y[1:(n*.5),(o-o1+1):o] <- rbinom((n*o1*.5),1,p)
y[1:(n*.5),1:(o-o1)] <- rbinom((o-o1)*n*.5,1,r)
y[(n*.5+1):n,(o-o1+1):o] <- rbinom((n*o1*.5),1,fp)
type <- c((o-o1),o1,0) ### vector with the number of each data type
site <- c(rep(1,n*.5*.8),rep(0,n*.5*.2),rep(1,n*.5*.2),rep(0,n*.8*.5))
occ <- matrix(c(rep(0,n*(o-o1)),rep(1,n*o1)),n,o)
site <- data.frame(habitat = site)
occ <- list(METH = occ)

umf1 <- unmarkedFrameOccuFP(y,site,occ, type = type)

m1 <- occuFP(detformula = ~ METH, FPformula = ~1, stateformula = ~ habitat, data = umf1)

```

unmarkedFrameOccuMS	<i>Organize data for the multi-state occupancy model fit by occuMS</i>
---------------------	--

Description

Organizes multi-state occupancy data (currently single-season only) along with covariates. This S4 class is required by the data argument of [occuMS](#)

Usage

```

unmarkedFrameOccuMS(y, siteCovs=NULL, obsCovs=NULL,
                     numPrimary=1, yearlySiteCovs=NULL)

```

Arguments

y	An MxR matrix of multi-state occupancy data for a species, where M is the number of sites and R is the maximum number of observations per site (across all primary and secondary periods, if you have multi-season data). Values in y should be integers ranging from 0 (non-detection) to the number of total states - 1. For example, if you have 3 occupancy states, y should contain only values 0, 1, or 2.
siteCovs	A data.frame of covariates that vary at the site level. This should have M rows and one column per covariate

obsCovs	Either a named list of data.frames of covariates that vary within sites, or a data.frame with MxR rows in the ordered by site-observation (if single-season) or site-primary period-observation (if multi-season).
numPrimary	Number of primary time periods (e.g. seasons) for the dynamic or multi-season version of the model. There should be an equal number of secondary periods in each primary period.
yearlySiteCovs	A data frame with one column per covariate that varies among sites and primary periods (e.g. years). It should have MxT rows where M is the number of sites and T the number of primary periods, ordered by site-primary period. These covariates only used for dynamic (multi-season) models.

Details

unmarkedFrameOccuMS is the S4 class that holds data to be passed to the [occuMS](#) model-fitting function.

Value

an object of class unmarkedFrameOccuMS

Author(s)

Ken Kellner <contact@kenkellner.com>

See Also

[unmarkedFrame-class](#), [unmarkedFrame](#), [occuMS](#)

Examples

```
# Fake data
#Parameters
N <- 100; J <- 3; S <- 3
psi <- c(0.5,0.3,0.2)
p11 <- 0.4; p12 <- 0.25; p22 <- 0.3

#Simulate state
z <- sample(0:2, N, replace=TRUE, prob=psi)

#Simulate detection
y <- matrix(0,nrow=N,ncol=J)
for (n in 1:N){
  probs <- switch(z[n]+1,
    c(0,0,0),
    c(1-p11,p11,0),
    c(1-p12-p22,p12,p22))

  if(z[n]>0){
    y[n,] <- sample(0:2, J, replace=TRUE, probs)
  }
}
```



```

}

#Covariates
site_covs <- as.data.frame(matrix(rnorm(N*2),ncol=2)) # nrow = # of sites
obs_covs <- as.data.frame(matrix(rnorm(N*J*2),ncol=2)) # nrow = N*J

#Build unmarked frame
umf <- unmarkedFrameOccuMS(y=y,siteCovs=site_covs,obsCovs=obs_covs)

umf                # look at data
summary(umf)       # summarize
plot(umf)          # visualize
umf@numStates      # check number of occupancy states detected

```

unmarkedFrameOccuMulti

Organize data for the multispecies occupancy model fit by occuMulti

Description

Organizes detection, non-detection data for multiple species along with the covariates. This S4 class is required by the data argument of [occuMulti](#)

Usage

```
unmarkedFrameOccuMulti(y, siteCovs=NULL, obsCovs=NULL,
                        maxOrder, mapInfo)
```

Arguments

y	A list (optionally a named list) of length S where each element is an MxJ matrix of the detection, non-detection data for one species, where M is the number of sites, J is the maximum number of sampling periods per site, and S is the number of species in the analysis.
siteCovs	A data.frame of covariates that vary at the site level. This should have M rows and one column per covariate
obsCovs	Either a named list of data.frames of covariates that vary within sites, or a data.frame with MxJ rows in site-major order.
maxOrder	Optional; specify maximum interaction order. Defaults to number of species (all possible interactions). Reducing this value may speed up creation of unmarked frame if you aren't interested in higher-order interactions.
mapInfo	Currently ignored

Details

unmarkedFrameOccuMulti is the S4 class that holds data to be passed to the [occuMulti](#) model-fitting function.

Arguments

<code>y</code>	An MxR matrix of multi-state occupancy data for a species, where M is the number of sites and R is the maximum number of observations per site (across all primary periods and observations, if you have multi-season data). Values in <code>y</code> should be positive.
<code>surveyLength</code>	The maximum length of a survey, in the same units as <code>y</code> . You can provide either a single value (if all surveys had the same max length), or a matrix matching the dimensions of <code>y</code> (if surveys had different max lengths).
<code>siteCovs</code>	A <code>data.frame</code> of covariates that vary at the site level. This should have M rows and one column per covariate
<code>obsCovs</code>	Either a named list of <code>data.frames</code> of covariates that vary within sites, or a <code>data.frame</code> with MxR rows in the ordered by site-observation (if single-season) or site-primary period-observation (if multi-season).
<code>numPrimary</code>	Number of primary time periods (e.g. seasons) for the dynamic or multi-season version of the model. There should be an equal number of secondary periods in each primary period.
<code>yearlySiteCovs</code>	A data frame with one column per covariate that varies among sites and primary periods (e.g. years). It should have MxT rows where M is the number of sites and T the number of primary periods, ordered by site-primary period. These covariates only used for dynamic (multi-season) models.

Details

`unmarkedFrameOccuTTD` is the S4 class that holds data to be passed to the `occuTTD` model-fitting function.

Value

an object of class `unmarkedFrameOccuTTD`

Author(s)

Ken Kellner <contact@kenkellner.com>

Examples

```
# For a single-season model
N <- 100 #Number of sites
psi <- 0.4 #Occupancy probability
lam <- 7 #Parameter for exponential distribution of time to detection
Tmax <- 10 #Maximum survey length

z <- rbinom(N, 1, psi) #Simulate occupancy
y <- rexp(N, 1/lam) #Simulate time to detection
y[z==0] <- Tmax
y[y>Tmax] <- Tmax
```

```
sc <- as.data.frame(matrix(rnorm(N*2),ncol=2)) #Site covs
oc <- as.data.frame(matrix(rnorm(N*2),ncol=2)) #obs covs

umf <- unmarkedFrameOccuTTD(y=y, surveyLength=Tmax, siteCovs=sc, obsCovs=oc)
```

unmarkedFramePCO	<i>Create an object of class unmarkedFramePCO that contains data used by pcountOpen.</i>
------------------	--

Description

Organizes repeated count data along with the covariates and possibly the dates on which each survey was conducted. This S4 class is required by the data argument of [pcountOpen](#)

Usage

```
unmarkedFramePCO(y, siteCovs=NULL, obsCovs=NULL, yearlySiteCovs, mapInfo,
  numPrimary, primaryPeriod)
```

Arguments

y	An MxJT matrix of the repeated count data, where M is the number of sites, J is the maximum number of secondary sampling periods per site and T is the maximum number of primary sampling periods per site.
siteCovs	A data.frame of covariates that vary at the site level. This should have M rows and one column per covariate
obsCovs	Either a named list of data.frames of covariates that vary within sites, or a data.frame with MxJT rows in site-major order.
yearlySiteCovs	Either a named list of MxT data.frames , or a site-major data.frame with MT rows and 1 column per covariate.
mapInfo	Currently ignored
numPrimary	Maximum number of observed primary periods for each site
primaryPeriod	matrix of integers indicating the primary period of each survey.

Details

unmarkedFramePCO is the S4 class that holds data to be passed to the [pcountOpen](#) model-fitting function.

The unmarkedFramePCO class is similar to the unmarkedFramePCount class except that it contains the dates for each survey, which needs to be supplied .

Value

an object of class unmarkedFramePCO

See Also

[unmarkedFrame-class](#), [unmarkedFrame](#), [pcountOpen](#)

Examples

```
# Repeated count data with 5 primary periods and
# no secondary sampling periods (ie J=1)
y1 <- matrix(c(
  0, 2, 3, 2, 0,
  2, 2, 3, 1, 1,
  1, 1, 0, 0, 3,
  0, 0, 0, 0, 0), nrow=4, ncol=5, byrow=TRUE)

# Site-specific covariates
sc1 <- data.frame(x1 = 1:4, x2 = c('A','A','B','B'))

# Observation-specific covariates
oc1 <- list(
  x3 = matrix(1:5, nrow=4, ncol=5, byrow=TRUE),
  x4 = matrix(letters[1:5], nrow=4, ncol=5, byrow=TRUE))

# Primary periods of surveys
primaryPeriod1 <- matrix(as.integer(c(
  1, 2, 5, 7, 8,
  1, 2, 3, 4, 5,
  1, 2, 4, 5, 6,
  1, 3, 5, 6, 7)), nrow=4, ncol=5, byrow=TRUE)

# Create the unmarkedFrame
umf1 <- unmarkedFramePCO(y=y1, siteCovs=sc1, obsCovs=oc1, numPrimary=5,
  primaryPeriod=primaryPeriod1)

# Take a look
umf1
summary(umf1)

# Repeated count data with 4 primary periods and
# no 2 secondary sampling periods (ie J=2)
y2 <- matrix(c(
  0,0, 2,2, 3,2, 2,2,
  2,2, 2,1, 3,2, 1,1,
  1,0, 1,1, 0,0, 0,0,
  0,0, 0,0, 0,0, 0,0), nrow=4, ncol=8, byrow=TRUE)
```

```

# Site-specific covariates
sc2 <- data.frame(x1 = 1:4, x2 = c('A','A','B','B'))

# Observation-specific covariates
oc2 <- list(
  x3 = matrix(1:8, nrow=4, ncol=8, byrow=TRUE),
  x4 = matrix(letters[1:8], nrow=4, ncol=8, byrow=TRUE))

# Yearly-site covariates
ysc <- list(
  x5 = matrix(c(
    1,2,3,4,
    1,2,3,4,
    1,2,3,4,
    1,2,3,4), nrow=4, ncol=4, byrow=TRUE))

# Primary periods of surveys
primaryPeriod2 <- matrix(as.integer(c(
  1,2,5,7,
  1,2,3,4,
  1,2,4,5,
  1,3,5,6)), nrow=4, ncol=4, byrow=TRUE)

# Create the unmarkedFrame
umf2 <- unmarkedFramePCO(y=y2, siteCovs=sc2, obsCovs=oc2,
  yearlySiteCovs=ysc,
  numPrimary=4, primaryPeriod=primaryPeriod2)

# Take a look
umf2
summary(umf2)

```

unmarkedFramePCount *Organize data for the N-mixture model fit by pcount*

Description

Organizes repeated count data along with the covariates. This S4 class is required by the data argument of [pcount](#)

Usage

```
unmarkedFramePCount(y, siteCovs=NULL, obsCovs=NULL, mapInfo)
```

Arguments

y An RxJ matrix of the repeated count data, where R is the number of sites, J is the maximum number of sampling periods per site.

siteCovs	A data.frame of covariates that vary at the site level. This should have R rows and one column per covariate
obsCovs	Either a named list of data.frames of covariates that vary within sites, or a data.frame with RxJ rows in site-major order.
mapInfo	Currently ignored

Details

unmarkedFramePCount is the S4 class that holds data to be passed to the [pcount](#) model-fitting function.

Value

an object of class unmarkedFramePCount

See Also

[unmarkedFrame-class](#), [unmarkedFrame](#), [pcount](#)

Examples

```
# Fake data
R <- 4 # number of sites
J <- 3 # number of visits
y <- matrix(c(
  1,2,0,
  0,0,0,
  1,1,1,
  2,2,1), nrow=R, ncol=J, byrow=TRUE)
y

site.covs <- data.frame(x1=1:4, x2=factor(c('A','B','A','B')))
site.covs

obs.covs <- list(
  x3 = matrix(c(
    -1,0,1,
    -2,0,0,
    -3,1,0,
    0,0,0), nrow=R, ncol=J, byrow=TRUE),
  x4 = matrix(c(
    'a','b','c',
    'd','b','a',
    'a','a','c',
    'a','b','a'), nrow=R, ncol=J, byrow=TRUE))
obs.covs

umf <- unmarkedFramePCount(y=y, siteCovs=site.covs,
  obsCovs=obs.covs)      # organize data
umf                      # take a l
```

```
summary(umf)           # summarize data
fm <- pcount(~1 ~1, umf, K=10) # fit a model
```

unmarkedMultFrame	<i>Create an unmarkedMultFrame, unmarkedFrameGMM, unmarkedFrameGDS, or unmarkedFrameGPC object</i>
-------------------	--

Description

These functions construct unmarkedFrames for data collected during primary and secondary sampling periods.

Usage

```
unmarkedMultFrame(y, siteCovs, obsCovs, numPrimary, yearlySiteCovs)
unmarkedFrameGMM(y, siteCovs, obsCovs, numPrimary, yearlySiteCovs, type,
  obsToY, piFun)
unmarkedFrameGDS(y, siteCovs, numPrimary, yearlySiteCovs, dist.breaks,
  survey, unitsIn, tlength)
unmarkedFrameGPC(y, siteCovs, obsCovs, numPrimary, yearlySiteCovs)
```

Arguments

y	A matrix of the observed data.
siteCovs	Data frame of covariates that vary at the site level.
obsCovs	Data frame of covariates that vary within site-year-observation level.
numPrimary	Number of primary time periods (seasons in the multiseason model).
yearlySiteCovs	Data frame containing covariates at the site-year level.
type	Set to "removal" for constant-interval removal sampling, "double" for standard double observer sampling, or "depDouble" for dependent double observer sampling. This should not be specified for other types of survey designs.
obsToY	A matrix specifying relationship between observation-level covariates and response matrix
piFun	A function converting an MxJ matrix of detection probabilities into an MxJ matrix of multinomial cell probabilities.
dist.breaks	see unmarkedFrameDS
survey	see unmarkedFrameDS
unitsIn	see unmarkedFrameDS
tlength	see unmarkedFrameDS

Details

unmarkedMultFrame objects are used by [colext](#).

unmarkedFrameGMM objects are used by [gmultmix](#).

unmarkedFrameGDS objects are used by [gdistsamp](#).

unmarkedFrameGPC objects are used by [gpcount](#).

For a study with M sites, T years, and a maximum of J observations per site-year, the data can be supplied in a variety of ways but are stored as follows. y is an $M \times TJ$ matrix, with each row corresponding to a site. `siteCovs` is a data frame with M rows. `yearlySiteCovs` is a data frame with MT rows which are in site-major, year-minor order. `obsCovs` is a data frame with MTJ rows, which are ordered by site-year-observation, so that a column of `obsCovs` corresponds to `as.vector(t(y))`, element-by-element. The number of years must be specified in `numPrimary`.

If the data are in long format, the convenience function [formatMult](#) is useful for creating the unmarkedMultFrame.

unmarkedFrameGMM and unmarkedFrameGDS are superclasses of unmarkedMultFrame containing information on the survey design used that resulted in multinomial outcomes. For unmarkedFrameGMM and constant-interval removal sampling, you can set `type="removal"` and ignore the arguments `obsToY` and `piFun`. Similarly, for double-observer sampling, setting `type="double"` or `type="depDouble"` will automatically create an appropriate `obsToY` matrix and [piFuns](#). For all other situations, the `type` argument of unmarkedFrameGMM should be ignored and the `obsToY` and `piFun` arguments must be specified. `piFun` must be a function that converts an $M \times J$ matrix of detection probabilities into an $M \times J$ matrix of multinomial cell probabilities. `obsToY` is a matrix describing how the `obsCovs` relate to the observed counts y . For further discussion and examples see the help page for [multinomPois](#) and [piFuns](#).

unmarkedFrameGMM and unmarkedFrameGDS objects can be created from an unmarkedMultFrame using the "as" conversion method. See examples.

Value

an unmarkedMultFrame or unmarkedFrameGMM object

Note

Data used with [colext](#), [gmultmix](#), and [gdistsamp](#) may be collected during a single year, so `yearlySiteCovs` may be a misnomer in some cases.

See Also

[formatMult](#), [colext](#), [gmultmix](#), [gpcount](#)

Examples

```
n <- 50 # number of sites
T <- 4  # number of primary periods
J <- 3  # number of secondary periods

site <- 1:50
```

```

years <- data.frame(matrix(rep(2010:2013, each=n), n, T))
years <- data.frame(lapply(years, as.factor))
occasions <- data.frame(matrix(rep(1:(J*T), each=n), n, J*T))

y <- matrix(0:1, n, J*T)

umf <- unmarkedMultFrame(y=y,
  siteCovs = data.frame(site=site),
  obsCovs=list(occasion=occasions),
  yearlySiteCovs=list(year=years),
  numPrimary=T)

umfGMM1 <- unmarkedFrameGMM(y=y,
  siteCovs = data.frame(site=site),
  obsCovs=list(occasion=occasions),
  yearlySiteCovs=data.frame(year=c(t(years))),
  # or: yearlySiteCovs=list(year=years),
  numPrimary=T, type="removal")

# A user-defined piFun calculating removal probs when time intervals differ.
instRemPiFun <- function(p) {
  M <- nrow(p)
  J <- ncol(p)
  pi <- matrix(NA, M, J)
  p[,1] <- pi[,1] <- 1 - (1 - p[,1])^2
  p[,2] <- 1 - (1 - p[,2])^3
  p[,3] <- 1 - (1 - p[,3])^5
  for(i in 2:J) {
    pi[,i] <- pi[, i - 1]/p[, i - 1] * (1 - p[, i - 1]) * p[, i]
  }
  return(pi)
}

# Associated obsToY matrix required by unmarkedFrameMPois
o2y <- diag(ncol(y))
o2y[upper.tri(o2y)] <- 1
o2y

umfGMM2 <- unmarkedFrameGMM(y=y,
  siteCovs = data.frame(site=site),
  obsCovs=list(occasion=occasions),
  yearlySiteCovs=data.frame(year=years),
  numPrimary=T, obsToY=o2y, piFun="instRemPiFun")

str(umfGMM2)

```

unmarkedRanef-class Class "unmarkedRanef"

Description

Stores the estimated posterior distributions of the latent abundance or occurrence variables.

Objects from the Class

Objects can be created by calls of the form [ranef](#).

Slots

post: An [array](#) with nSites rows and Nmax (K+1) columns and nPrimaryPeriod slices

Methods

bup signature(object = "unmarkedRanef"): Extract the Best Unbiased Predictors (BUPs) of the latent variables (abundance or occurrence state). Either the posterior mean or median can be requested using the stat argument.

confint signature(object = "unmarkedRanef"): Compute confidence intervals.

plot signature(x = "unmarkedRanef", y = "missing"): Plot the posteriors using [xyplot](#)

show signature(object = "unmarkedRanef"): Display the modes and confidence intervals

Warnings

Empirical Bayes methods can underestimate the variance of the posterior distribution because they do not account for uncertainty in the hyperparameters (lambda or psi). Simulation studies indicate that the posterior mode can exhibit (3-5 percent) negatively bias as a point estimator of site-specific abundance. It appears to be safer to use the posterior mean even though this will not be an integer in general.

References

Laird, N.M. and T.A. Louis. 1987. Empirical Bayes confidence intervals based on bootstrap samples. *Journal of the American Statistical Association* 82:739–750.

Carlin, B.P and T.A Louis. 1996. *Bayes and Empirical Bayes Methods for Data Analysis*. Chapman and Hall/CRC.

Royle, J.A and R.M. Dorazio. 2008. *Hierarchical Modeling and Inference in Ecology*. Academic Press.

See Also

[ranef](#)

Examples

```
showClass("unmarkedRanef")
```

vcov-methods

Methods for Function vcov in Package 'unmarked'

Description

Extract variance-covariance matrix from a fitted model.

Methods

object = "linCombOrBackTrans" See [linearComb-methods](#)

object = "unmarkedEstimate" See [unmarkedEstimate-class](#)

object = "unmarkedFit" A fitted model

vif

Compute Variance Inflation Factors for an unmarkedFit Object.

Description

Compute the variance inflation factors (VIFs) for covariates in one level of the model (i.e., occupancy or detection). Calculation of VIFs follows the approach of function vif in package car, using the correlation matrix of fitted model parameters.

Usage

```
vif(mod, type)
```

Arguments

mod An unmarked fit object.

type Level of the model for which to calculate VIFs (for example, 'state')

Value

A named vector of variance inflation factor values for each covariate.

[-methods

*Methods for bracket extraction [in Package 'unmarked'***Description**

Methods for bracket extraction [in Package 'unmarked'

Usage

```
## S4 method for signature 'unmarkedEstimateList,ANY,ANY,ANY'
x[i, j, drop]
## S4 method for signature 'unmarkedFit,ANY,ANY,ANY'
x[i, j, drop]
## S4 method for signature 'unmarkedFrame,numeric,numeric,missing'
x[i, j]
## S4 method for signature 'unmarkedFrame,list,missing,missing'
x[i, j]
## S4 method for signature 'unmarkedMultFrame,missing,numeric,missing'
x[i, j]
## S4 method for signature 'unmarkedMultFrame,numeric,missing,missing'
x[i, j]
## S4 method for signature 'unmarkedFrameGMM,numeric,missing,missing'
x[i, j]
## S4 method for signature 'unmarkedFrameGDS,numeric,missing,missing'
x[i, j]
## S4 method for signature 'unmarkedFramePCO,numeric,missing,missing'
x[i, j]
```

Arguments

x	Object of appropriate S4 class
i	Row numbers
j	Observation numbers (eg occasions, distance classes, etc...)
drop	Not currently used

Methods

x = "unmarkedEstimateList", i = "ANY", j = "ANY", drop = "ANY" Extract a unmarkedEstimate object from an unmarkedEstimateList by name (either 'det' or 'state')

x = "unmarkedFit", i = "ANY", j = "ANY", drop = "ANY" Extract a unmarkedEstimate object from an unmarkedFit by name (either 'det' or 'state')

x = "unmarkedFrame", i = "missing", j = "numeric", drop = "missing" Extract observations from an unmarkedFrame.

x = "unmarkedFrame", i = "numeric", j = "missing", drop = "missing" Extract rows from an unmarkedFrame

x = "unmarkedFrame", i = "numeric", j = "numeric", drop = "missing" Extract rows and observations from an unmarkedFrame

x = "unmarkedMultFrame", i = "missing", j = "numeric", drop = "missing" Extract primary sampling periods from an unmarkedMultFrame

x = "unmarkedFrame", i = "list", j = "missing", drop = "missing" List is the index of observations to subset for each site.

x = "unmarkedMultFrame", i = "numeric", j = "missing", drop = "missing" Extract rows (sites) from an unmarkedMultFrame

x = "unmarkedGMM", i = "numeric", j = "missing", drop = "missing" Extract rows (sites) from an unmarkedFrameGMM object

x = "unmarkedGDS", i = "numeric", j = "missing", drop = "missing" Extract rows (sites) from an unmarkedFrameGDS object

x = "unmarkedPCO", i = "numeric", j = "missing", drop = "missing" Extract rows (sites) from an unmarkedFramePCO object

Examples

```
data(mallard)
mallardUMF <- unmarkedFramePCount(mallard.y, siteCovs = mallard.site,
obsCovs = mallard.obs)
summary(mallardUMF)

mallardUMF[1:5,]
mallardUMF[,1:2]
mallardUMF[1:5, 1:2]
```

Index

- * **classes**
 - unmarkedEstimate-class, 115
 - unmarkedEstimateList-class, 116
 - unmarkedFit-class, 116
 - unmarkedFitList-class, 119
 - unmarkedFrame-class, 122
 - unmarkedRanef-class, 147
- * **datasets**
 - birds, 9
 - crossbill, 15
 - cruz, 19
 - frogs, 36
 - gf, 41
 - issj, 47
 - jay, 48
 - linetran, 51
 - mallard, 54
 - masspcru, 55
 - ovendata, 93
 - pointtran, 106
 - Switzerland, 114
- * **methods**
 - [-methods, 149
 - backTransform-methods, 8
 - coef-methods, 9
 - confint-methods, 14
 - fitted-methods, 31
 - getB-methods, 40
 - getFP-methods, 40
 - getP-methods, 40
 - linearComb-methods, 51
 - nonparboot-methods, 63
 - predict-methods, 108
 - ranef-methods, 109
 - SE-methods, 111
 - simulate-methods, 112
 - vcov-methods, 148
- * **models**
 - colext, 10
 - computeMPLElambda, 13
 - distsamp, 22
 - distsampOpen, 26
 - gdistsamp, 37
 - multinomPois, 57
 - multmixOpen, 59
 - occu, 65
 - occuFP, 67
 - occuMS, 69
 - occuMulti, 78
 - occuPEN, 82
 - occuPEN_CV, 85
 - occuRN, 87
 - occuTTD, 89
 - pcount, 96
 - pcountOpen, 100
- * **model**
 - gmultmix, 41
- * **package**
 - unmarked-package, 4
- * **utilities**
 - csvToUMF, 20
 - imputeMissing, 46
 - [,unmarkedEstimateList,ANY,ANY,ANY-method
([-methods), 149
 - [,unmarkedFit,ANY,ANY,ANY-method
([-methods), 149
 - [,unmarkedFrame,list,missing,missing-method
([-methods), 149
 - [,unmarkedFrame,missing,numeric,missing-method
([-methods), 149
 - [,unmarkedFrame,numeric,missing,missing-method
([-methods), 149
 - [,unmarkedFrame,numeric,numeric,missing-method
([-methods), 149
 - [,unmarkedFrameDSO,numeric,missing,missing-method
(unmarkedFrame-class), 122
 - [,unmarkedFrameGDS,numeric,missing,missing-method
([-methods), 149

- [,unmarkedFrameGMM,numeric,missing,missing-method (coef-methods),
([-methods), 149
- [,unmarkedFrameGPC,missing,numeric,missing-method (coef-methods), 149
- [,unmarkedFrameGPC,numeric,missing,missing-method (coef-methods), 149
- [,unmarkedFrameOccuMS,numeric,missing,missing-method (unmarkedFrame-class), 122
- [,unmarkedFrameOccuMulti,missing,numeric,missing-method (unmarkedFrame-class), 122
- [,unmarkedFrameOccuMulti,numeric,missing,missing-method (unmarkedFrame-class), 122
- [,unmarkedFrameOccuTTD,missing,numeric,missing-method (unmarkedFrame-class), 122
- [,unmarkedFrameOccuTTD,numeric,missing,missing-method (unmarkedFrame-class), 122
- [,unmarkedFramePCO,missing,numeric,missing-method ([-methods), 149
- [,unmarkedFramePCO,numeric,missing,missing-method ([-methods), 149
- [,unmarkedMultFrame,missing,numeric,missing-method ([-methods), 149
- [,unmarkedMultFrame,numeric,missing,missing-method ([-methods), 149
- [,unmarkedPostSamples,ANY,ANY,ANY-method (posteriorSamples), 107
- [-methods, 149
- array, 147
- backTransform, 64
- backTransform (backTransform-methods), 8
- backTransform,unmarkedEstimate-method (backTransform-methods), 8
- backTransform,unmarkedFit-method (backTransform-methods), 8
- backTransform,unmarkedLinComb-method (backTransform-methods), 8
- backTransform-methods, 8
- birds, 9
- bup (unmarkedRanef-class), 147
- bup,unmarkedRanef-method (unmarkedRanef-class), 147
- catbird (birds), 9
- coef,linCombOrBackTrans-method (coef-methods), 9
- coef,unmarkedEstimate-method (coef-methods), 9
- coef,unmarkedFit-method (coef-methods), 9
- coef,unmarkedFitList-method (unmarkedFitList-class), 119
- coef,unmarkedModSel-method (modSel), 56
- coef-methods, 9
- computeMPLambda, 13, 84
- confint,unmarkedBackTrans-method (confint-methods), 14
- confint,unmarkedEstimate-method (confint-methods), 14
- confint,unmarkedFit-method (confint-methods), 14
- confint,unmarkedLinComb-method (confint-methods), 14
- confint,unmarkedRanef-method (unmarkedRanef-class), 147
- confint-methods, 14
- coordinates (unmarkedFrame-class), 122
- coordinates,unmarkedFrame-method (unmarkedFrame-class), 122
- coordinates (unmarkedFrame-class), 122
- crossbill, 15
- crossVal, 17
- crossVal,unmarkedFit-method (crossVal), 17
- crossVal,unmarkedFitList-method (crossVal), 17
- crossVal-methods (crossVal), 17
- cruz, 19, 48
- csvToUMF, 5, 20, 36
- data.frame, 121, 125–130, 133–137, 139, 140, 143
- detFuns, 21, 24
- distsamp, 4, 5, 21, 22, 22, 28, 32, 33, 38, 50, 112, 113, 116, 121, 124, 125
- distsampOpen, 26, 126, 127
- doublePiFun, 42, 58
- doublePiFun (piFuns), 104
- dexp (detFuns), 21
- drhaz (detFuns), 21
- drhn (detFuns), 21
- dxexp (detFuns), 21
- dxhaz (detFuns), 21
- dxhn (detFuns), 21
- fitList, 18, 24, 30, 56, 119, 120

- fitted,unmarkedFit-method
(fitted-methods), 31
- fitted,unmarkedFitColExt-method
(fitted-methods), 31
- fitted,unmarkedFitDS-method
(fitted-methods), 31
- fitted,unmarkedFitDSO-method
(fitted-methods), 31
- fitted,unmarkedFitGMM-method
(fitted-methods), 31
- fitted,unmarkedFitOccu-method
(fitted-methods), 31
- fitted,unmarkedFitOccuFP-method
(fitted-methods), 31
- fitted,unmarkedFitOccuMS-method
(fitted-methods), 31
- fitted,unmarkedFitOccuMulti-method
(fitted-methods), 31
- fitted,unmarkedFitOccuRN-method
(fitted-methods), 31
- fitted,unmarkedFitOccuTTD-method
(fitted-methods), 31
- fitted,unmarkedFitPCO-method
(fitted-methods), 31
- fitted,unmarkedFitPCount-method
(fitted-methods), 31
- fitted-methods, 31
- formatDistData, 24, 32
- formatLong (formatWideLong), 35
- formatMult, 11, 34, 145
- formatWide (formatWideLong), 35
- formatWideLong, 35
- formula, 66
- frog2001pcru (frogs), 36
- frog2001pfer (frogs), 36
- frogs, 36
- gdistsamp, 4, 23, 24, 28, 32, 33, 37, 46, 145
- getB (getB-methods), 40
- getB,unmarkedFitOccuFP-method
(getB-methods), 40
- getB-methods, 40
- getData (unmarkedFit-class), 116
- getData,unmarkedFit-method
(unmarkedFit-class), 116
- getFP (getFP-methods), 40
- getFP,unmarkedFitOccuFP-method
(getFP-methods), 40
- getFP-methods, 40
- getP (getP-methods), 40
- getP,unmarkedFit-method (getP-methods),
40
- getP,unmarkedFitColExt-method
(getP-methods), 40
- getP,unmarkedFitDS-method
(getP-methods), 40
- getP,unmarkedFitDSO-method
(getP-methods), 40
- getP,unmarkedFitGDS-method
(getP-methods), 40
- getP,unmarkedFitGMM-method
(getP-methods), 40
- getP,unmarkedFitGPC-method
(getP-methods), 40
- getP,unmarkedFitMMO-method
(getP-methods), 40
- getP,unmarkedFitMPois-method
(getP-methods), 40
- getP,unmarkedFitOccuFP-method
(getP-methods), 40
- getP,unmarkedFitOccuMS-method
(getP-methods), 40
- getP,unmarkedFitOccuMulti-method
(getP-methods), 40
- getP,unmarkedFitOccuTTD-method
(getP-methods), 40
- getP,unmarkedFitPCO-method
(getP-methods), 40
- getP-methods, 40
- getY (unmarkedFrame-class), 122
- getY,unmarkedFit-method
(unmarkedFit-class), 116
- getY,unmarkedFitColExt-method
(unmarkedFit-class), 116
- getY,unmarkedFitOccu-method
(unmarkedFit-class), 116
- getY,unmarkedFitOccuMulti-method
(unmarkedFit-class), 116
- getY,unmarkedFitOccuRN-method
(unmarkedFit-class), 116
- getY,unmarkedFrame-method
(unmarkedFrame-class), 122
- gf, 41
- gmultmix, 5, 41, 46, 61, 62, 104, 129, 145
- gpcount, 4, 44, 145
- grexp (detFuns), 21
- grhaz (detFuns), 21

- grhn (detFuns), 21
- gxexp (detFuns), 21
- gxhaz (detFuns), 21
- gxhn (detFuns), 21
- head, unmarkedFrame-method
(unmarkedFrame-class), 122
- hessian (unmarkedFit-class), 116
- hessian, unmarkedFit-method
(unmarkedFit-class), 116
- hist, unmarkedFitDS-method
(unmarkedFit-class), 116
- hist, unmarkedFrameDS-method
(unmarkedFrame-class), 122
- imputeMissing, 46
- integrate, 23, 38
- issj, 47
- jay, 48
- lambda2psi, 50
- linearComb, 64
- linearComb (linearComb-methods), 51
- linearComb, unmarkedEstimate, matrixOrVector-method
(linearComb-methods), 51
- linearComb, unmarkedFit, matrixOrVector-method
(linearComb-methods), 51
- linearComb-methods, 51
- linetran, 51
- logLik (unmarkedFit-class), 116
- logLik, unmarkedFit-method
(unmarkedFit-class), 116
- LRT (unmarkedFit-class), 116
- LRT, unmarkedFit, unmarkedFit-method
(unmarkedFit-class), 116
- makeCrPiFun (makePiFuns), 52
- makeCrPiFunMb (makePiFuns), 52
- makeCrPiFunMh (makePiFuns), 52
- makePiFuns, 52, 105
- makeRemPiFun (makePiFuns), 52
- mallard, 54
- mapInfo (unmarkedFrame-class), 122
- masspcru, 55
- mle (unmarkedFit-class), 116
- mle, unmarkedFit-method
(unmarkedFit-class), 116
- modSel, 56, 66, 68
- modSel, unmarkedFitList-method
(unmarkedFitList-class), 119
- modSel-methods (modSel), 56
- multinomPois, 5, 43, 50, 57, 61, 62, 104, 113,
121, 129–131, 145
- multmixOpen, 59, 128, 129
- names, unmarkedEstimateList-method
(unmarkedEstimateList-class),
116
- names, unmarkedFit-method
(unmarkedFit-class), 116
- nllFun (unmarkedFit-class), 116
- nllFun, unmarkedFit-method
(unmarkedFit-class), 116
- nonparboot, 11, 14, 84, 86
- nonparboot (nonparboot-methods), 63
- nonparboot, unmarkedFit-method
(nonparboot-methods), 63
- nonparboot, unmarkedFitColExt-method
(nonparboot-methods), 63
- nonparboot, unmarkedFitDS-method
(nonparboot-methods), 63
- nonparboot, unmarkedFitGDS-method
(nonparboot-methods), 63
- nonparboot, unmarkedFitGMM-method
(nonparboot-methods), 63
- nonparboot, unmarkedFitMPois-method
(nonparboot-methods), 63
- nonparboot, unmarkedFitOccu-method
(nonparboot-methods), 63
- nonparboot, unmarkedFitOccuPEN-method
(nonparboot-methods), 63
- nonparboot, unmarkedFitOccuPEN_CV-method
(nonparboot-methods), 63
- nonparboot, unmarkedFitOccuRN-method
(nonparboot-methods), 63
- nonparboot, unmarkedFitOccuTTD-method
(nonparboot-methods), 63
- nonparboot, unmarkedFitPC0-method
(nonparboot-methods), 63
- nonparboot, unmarkedFitPCount-method
(nonparboot-methods), 63
- nonparboot-methods, 63
- numSites (unmarkedFrame-class), 122
- numSites, unmarkedFrame-method
(unmarkedFrame-class), 122
- numY (unmarkedFrame-class), 122

- numY, unmarkedFrame-method
(unmarkedFrame-class), 122
- obsCovs (unmarkedFrame-class), 122
- obsCovs, unmarkedFrame-method
(unmarkedFrame-class), 122
- obsCovs<- (unmarkedFrame-class), 122
- obsCovs<- , unmarkedFrame-method
(unmarkedFrame-class), 122
- obsNum (unmarkedFrame-class), 122
- obsNum, unmarkedFrame-method
(unmarkedFrame-class), 122
- obsToY (unmarkedFrame-class), 122
- obsToY, unmarkedFrame-method
(unmarkedFrame-class), 122
- obsToY<- (unmarkedFrame-class), 122
- obsToY<- , unmarkedFrame-method
(unmarkedFrame-class), 122
- occu, 4, 5, 14, 32, 64, 65, 67, 83, 84, 86, 113, 132–134
- occuFP, 4, 67, 134
- occuMS, 69, 135, 136
- occuMulti, 4, 78, 137, 138
- occuPEN, 13, 14, 82, 86
- occuPEN_CV, 14, 84, 85
- occuRN, 4, 5, 32, 64, 87, 113, 132–134
- occuTTD, 89, 138, 139
- optim, 10, 13, 23, 27, 38, 42, 45, 58, 61, 65, 67, 70, 78, 83, 85, 88, 90, 96, 99, 101, 102, 116
- ovendata, 93
- parboot, 24, 66, 68, 94, 97, 113
- parboot, unmarkedFit-method
(unmarkedFit-class), 116
- parboot, unmarkedFitOccuMulti-method
(unmarkedFit-class), 116
- pcount, 4, 5, 32, 50, 96, 103, 113, 142, 143
- pcount.spHDS, 98
- pcountOpen, 5, 97, 100, 140, 141
- pcru.bin (frogs), 36
- pcru.data (frogs), 36
- pcru.y (frogs), 36
- pfer.bin (frogs), 36
- pfer.data (frogs), 36
- pfer.y (frogs), 36
- piFuns, 43, 52, 58, 104, 131, 145
- plot, parboot, missing-method (parboot), 94
- plot, profile, missing-method
(unmarkedFit-class), 116
- plot, unmarkedFit, missing-method
(unmarkedFit-class), 116
- plot, unmarkedFitOccuMulti, missing-method
(unmarkedFit-class), 116
- plot, unmarkedFrame, missing-method
(unmarkedFrame-class), 122
- plot, unmarkedFrameOccuMulti, missing-method
(unmarkedFrame-class), 122
- plot, unmarkedFrameOccuTTD, missing-method
(unmarkedFrame-class), 122
- plot, unmarkedRanef, missing-method
(unmarkedRanef-class), 147
- pointtran, 106
- posteriorSamples, 107, 108
- posteriorSamples, unmarkedFit-method
(posteriorSamples), 107
- posteriorSamples, unmarkedRanef-method
(posteriorSamples), 107
- posteriorSamples-methods
(posteriorSamples), 107
- powerAnalysis (unmarkedFrame-class), 122
- powerAnalysis, formula, unmarkedFramePCount, numeric-method
(unmarkedFrame-class), 122
- predict, 8, 107
- predict (predict-methods), 108
- predict, ANY-method (predict-methods), 108
- predict, unmarkedFit-method
(predict-methods), 108
- predict, unmarkedFitColExt-method
(predict-methods), 108
- predict, unmarkedFitDSO-method
(predict-methods), 108
- predict, unmarkedFitGDS-method
(predict-methods), 108
- predict, unmarkedFitGMM-method
(predict-methods), 108
- predict, unmarkedFitList-method
(predict-methods), 108
- predict, unmarkedFitOccuFP-method
(predict-methods), 108
- predict, unmarkedFitOccuMS-method
(predict-methods), 108
- predict, unmarkedFitOccuMulti-method
(predict-methods), 108
- predict, unmarkedFitOccuTTD-method

- (predict-methods), 108
- predict, unmarkedFitPCO-method
 - (predict-methods), 108
- predict, unmarkedFitPCount-method
 - (predict-methods), 108
- predict, unmarkedRanef-method
 - (predict-methods), 108
- predict-methods, 108
- profile, unmarkedFit-method
 - (unmarkedFit-class), 116
- projected (unmarkedFit-class), 116
- projected, unmarkedFitColExt-method
 - (unmarkedFit-class), 116
- projection (unmarkedFrame-class), 122
- projection, unmarkedFrame-method
 - (unmarkedFrame-class), 122
- ranef, 24, 95, 97, 107, 108, 147
- ranef (ranef-methods), 109
- ranef, unmarkedFitColExt-method
 - (ranef-methods), 109
- ranef, unmarkedFitDS-method
 - (ranef-methods), 109
- ranef, unmarkedFitDSO-method
 - (ranef-methods), 109
- ranef, unmarkedFitGDS-method
 - (ranef-methods), 109
- ranef, unmarkedFitGMM-method
 - (ranef-methods), 109
- ranef, unmarkedFitGMMorGDS-method
 - (ranef-methods), 109
- ranef, unmarkedFitGPC-method
 - (ranef-methods), 109
- ranef, unmarkedFitMMO-method
 - (ranef-methods), 109
- ranef, unmarkedFitMPois-method
 - (ranef-methods), 109
- ranef, unmarkedFitOccu-method
 - (ranef-methods), 109
- ranef, unmarkedFitOccuFP-method
 - (ranef-methods), 109
- ranef, unmarkedFitOccuMS-method
 - (ranef-methods), 109
- ranef, unmarkedFitOccuMulti-method
 - (ranef-methods), 109
- ranef, unmarkedFitOccuRN-method
 - (ranef-methods), 109
- ranef, unmarkedFitOccuTTD-method
 - (ranef-methods), 109
- ranef, unmarkedFitPCO-method
 - (ranef-methods), 109
- ranef, unmarkedFitPCount-method
 - (ranef-methods), 109
- ranef-methods, 109
- removalPiFun, 42, 58
- removalPiFun (piFuns), 104
- residuals, unmarkedFit-method
 - (unmarkedFit-class), 116
- residuals, unmarkedFitOccu-method
 - (unmarkedFit-class), 116
- residuals, unmarkedFitOccuFP-method
 - (unmarkedFit-class), 116
- residuals, unmarkedFitOccuMulti-method
 - (unmarkedFit-class), 116
- residuals, unmarkedFitOccuRN-method
 - (unmarkedFit-class), 116
- residuals, unmarkedFitOccuTTD-method
 - (unmarkedFit-class), 116
- sampleSize (unmarkedFit-class), 116
- sampleSize, unmarkedFit-method
 - (unmarkedFit-class), 116
- SE (SE-methods), 111
- SE, linCombOrBackTrans-method
 - (SE-methods), 111
- SE, unmarkedEstimate-method
 - (SE-methods), 111
- SE, unmarkedFit-method (SE-methods), 111
- SE, unmarkedFitList-method
 - (unmarkedFitList-class), 119
- SE, unmarkedModSel-method (modSel), 56
- SE-methods, 111
- show, parboot-method (parboot), 94
- show, unmarkedBackTrans-method
 - (backTransform-methods), 8
- show, unmarkedCrossVal-method
 - (crossVal), 17
- show, unmarkedCrossValList-method
 - (crossVal), 17
- show, unmarkedEstimate-method
 - (unmarkedEstimate-class), 115
- show, unmarkedEstimateList-method
 - (unmarkedEstimateList-class), 116
- show, unmarkedFit-method
 - (unmarkedFit-class), 116
- show, unmarkedFrame-method
 - (unmarkedFrame-class), 122

- show, unmarkedFrameOccuMulti-method
(unmarkedFrame-class), [122](#)
- show, unmarkedFrameOccuTTD-method
(unmarkedFrame-class), [122](#)
- show, unmarkedLinComb-method
(linearComb-methods), [51](#)
- show, unmarkedModSel-method (modSel), [56](#)
- show, unmarkedMultFrame-method
(unmarkedFrame-class), [122](#)
- show, unmarkedPostSamples-method
(posteriorSamples), [107](#)
- show, unmarkedRanef-method
(unmarkedRanef-class), [147](#)
- sight2perpdist, [24](#), [112](#)
- simulate, unmarkedFitColExt-method
(simulate-methods), [112](#)
- simulate, unmarkedFitDS-method
(simulate-methods), [112](#)
- simulate, unmarkedFitDSO-method
(simulate-methods), [112](#)
- simulate, unmarkedFitGDS-method
(simulate-methods), [112](#)
- simulate, unmarkedFitGMM-method
(simulate-methods), [112](#)
- simulate, unmarkedFitGPC-method
(simulate-methods), [112](#)
- simulate, unmarkedFitMMO-method
(simulate-methods), [112](#)
- simulate, unmarkedFitMPois-method
(simulate-methods), [112](#)
- simulate, unmarkedFitOccu-method
(simulate-methods), [112](#)
- simulate, unmarkedFitOccuFP-method
(simulate-methods), [112](#)
- simulate, unmarkedFitOccuMS-method
(simulate-methods), [112](#)
- simulate, unmarkedFitOccuMulti-method
(simulate-methods), [112](#)
- simulate, unmarkedFitOccuRN-method
(simulate-methods), [112](#)
- simulate, unmarkedFitOccuTTD-method
(simulate-methods), [112](#)
- simulate, unmarkedFitPCO-method
(simulate-methods), [112](#)
- simulate, unmarkedFitPCount-method
(simulate-methods), [112](#)
- simulate-methods, [112](#)
- siteCovs (unmarkedFrame-class), [122](#)
- siteCovs, unmarkedFrame-method
(unmarkedFrame-class), [122](#)
- siteCovs<- (unmarkedFrame-class), [122](#)
- siteCovs<- , unmarkedFrame-method
(unmarkedFrame-class), [122](#)
- smoothed (unmarkedFit-class), [116](#)
- smoothed, unmarkedFitColExt-method
(unmarkedFit-class), [116](#)
- SSE, [113](#)
- SSE, unmarkedFit-method (SSE), [113](#)
- SSE, unmarkedFitOccuMulti-method (SSE),
[113](#)
- SSE-methods (SSE), [113](#)
- summary, unmarkedEstimate-method
(unmarkedEstimate-class), [115](#)
- summary, unmarkedEstimateList-method
(unmarkedEstimateList-class),
[116](#)
- summary, unmarkedFit-method
(unmarkedFit-class), [116](#)
- summary, unmarkedFitDS-method
(unmarkedFit-class), [116](#)
- summary, unmarkedFitList-method
(unmarkedFitList-class), [119](#)
- summary, unmarkedFrame-method
(unmarkedFrame-class), [122](#)
- summary, unmarkedFrameDS-method
(unmarkedFrame-class), [122](#)
- summary, unmarkedFrameOccuMulti-method
(unmarkedFrame-class), [122](#)
- summary, unmarkedFrameOccuTTD-method
(unmarkedFrame-class), [122](#)
- summary, unmarkedModSel-method (modSel),
[56](#)
- summary, unmarkedMultFrame-method
(unmarkedFrame-class), [122](#)
- Switzerland, [17](#), [114](#)
- unmarked, [14](#), [20](#), [66](#), [68](#), [72](#), [80](#), [84](#), [86](#), [91](#)
- unmarked (unmarked-package), [4](#)
- unmarked-package, [4](#)
- unmarkedCrossVal-class (crossVal), [17](#)
- unmarkedCrossValList-class (crossVal),
[17](#)
- unmarkedEstimate
(unmarkedEstimate-class), [115](#)
- unmarkedEstimate-class, [115](#)
- unmarkedEstimateList-class, [116](#)
- unmarkedFit, [18](#), [116](#), [120](#), [123](#)

- unmarkedFit (unmarkedFit-class), 116
- unmarkedFit-class, 116
- unmarkedFitDS-class
 - (unmarkedFit-class), 116
- unmarkedFitDSO-class
 - (unmarkedFit-class), 116
- unmarkedFitGMM-class
 - (unmarkedFit-class), 116
- unmarkedFitList-class, 119
- unmarkedFitMMO-class
 - (unmarkedFit-class), 116
- unmarkedFitMPois-class
 - (unmarkedFit-class), 116
- unmarkedFitOccu-class
 - (unmarkedFit-class), 116
- unmarkedFitOccuFP-class
 - (unmarkedFit-class), 116
- unmarkedFitOccuMS-class
 - (unmarkedFit-class), 116
- unmarkedFitOccuMulti-class
 - (unmarkedFit-class), 116
- unmarkedFitOccuPEN-class
 - (unmarkedFit-class), 116
- unmarkedFitOccuPEN_CV-class
 - (unmarkedFit-class), 116
- unmarkedFitOccuTTD-class
 - (unmarkedFit-class), 116
- unmarkedFitPCO-class
 - (unmarkedFit-class), 116
- unmarkedFitPCount-class
 - (unmarkedFit-class), 116
- unmarkedFrame, 5, 33, 65, 67, 71, 78, 83, 86, 120, 122, 123, 125, 127, 129, 131, 133, 134, 136, 138, 141, 143
- unmarkedFrame-class, 122
- unmarkedFrameDS, 24, 121, 124, 144
- unmarkedFrameDS-class
 - (unmarkedFrame-class), 122
- unmarkedFrameDSO, 26, 28, 126
- unmarkedFrameDSO-class
 - (unmarkedFrame-class), 122
- unmarkedFrameGDS, 33, 38
- unmarkedFrameGDS (unmarkedMultFrame), 144
- unmarkedFrameGDS-class
 - (unmarkedFrame-class), 122
- unmarkedFrameGMM, 42, 43
- unmarkedFrameGMM (unmarkedMultFrame), 144
- unmarkedFrameGMM-class
 - (unmarkedFrame-class), 122
- unmarkedFrameGPC, 43, 45, 46
- unmarkedFrameGPC (unmarkedMultFrame), 144
- unmarkedFrameGPC-class
 - (unmarkedFrame-class), 122
- unmarkedFrameMMO, 60–62, 128
- unmarkedFrameMMO-class
 - (unmarkedFrame-class), 122
- unmarkedFrameMPois, 58, 130
- unmarkedFrameMPois-class
 - (unmarkedFrame-class), 122
- unmarkedFrameOccu, 13, 14, 65, 66, 83–86, 88, 121, 132
- unmarkedFrameOccu-class
 - (unmarkedFrame-class), 122
- unmarkedFrameOccuFP, 67, 68, 134
- unmarkedFrameOccuMS, 70–72, 135
- unmarkedFrameOccuMS-class
 - (unmarkedFrame-class), 122
- unmarkedFrameOccuMulti, 78, 80, 137
- unmarkedFrameOccuMulti-class
 - (unmarkedFrame-class), 122
- unmarkedFrameOccuTTD, 90, 91, 138
- unmarkedFrameOccuTTD-class
 - (unmarkedFrame-class), 122
- unmarkedFramePCO, 101, 103, 140
- unmarkedFramePCO-class
 - (unmarkedFrame-class), 122
- unmarkedFramePCount, 97, 121, 142
- unmarkedFramePCount-class
 - (unmarkedFrame-class), 122
- unmarkedModSel-class (modSel), 56
- unmarkedMultFrame, 10, 11, 35, 144
- unmarkedMultFrame-class
 - (unmarkedFrame-class), 122
- unmarkedPostSamples-class
 - (posteriorSamples), 107
- unmarkedRanef-class, 109, 110, 147
- update, unmarkedFit-method
 - (unmarkedFit-class), 116
- update, unmarkedFitColExt-method
 - (unmarkedFit-class), 116
- update, unmarkedFitGMM-method
 - (unmarkedFit-class), 116
- update, unmarkedFitOccuMS-method

- (unmarkedFit-class), [116](#)
- update, unmarkedFitOccuMulti-method
 - (unmarkedFit-class), [116](#)
- update, unmarkedFitOccuTTD-method
 - (unmarkedFit-class), [116](#)
- update, unmarkedFitPCOrDSO-method
 - (unmarkedFit-class), [116](#)
- vcov, [64](#)
- vcov, linCombOrBackTrans-method
 - (vcov-methods), [148](#)
- vcov, unmarkedEstimate-method
 - (vcov-methods), [148](#)
- vcov, unmarkedFit-method (vcov-methods),
[148](#)
- vcov-methods, [148](#)
- vif, [148](#)
- woodthrush (birds), [9](#)
- xyplot, [147](#)
- yearlySiteCovs (unmarkedMultFrame), [144](#)
- yearlySiteCovs, unmarkedMultFrame-method
 - (unmarkedMultFrame), [144](#)
- yearlySiteCovs<- (unmarkedMultFrame),
[144](#)
- yearlySiteCovs<-, unmarkedMultFrame-method
 - (unmarkedMultFrame), [144](#)