

Package ‘inlabru’

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Description Facilitates spatial modeling using integrated nested Laplace approximation via the INLA package (<<http://www.r-inla.org>>). Additionally, implements a log Gaussian Cox process likelihood for modeling univariate and spatial point processes based on ecological survey data. See Yuan Yuan, Fabian E. Bachl, Finn Lindgren, David L. Borchers, Janine B. Illian, Stephen T. Buckland, Havard Rue, Tim Gerrodette (2017), <[arXiv:1604.06013](https://arxiv.org/abs/1604.06013)>.

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Imports rgdal, rgeos, utils

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R topics documented:

bincount	3
bru	4
bru.components	6
bru.options	8
cprod	9
deltaIC	10
devel.cvmeasure	11
generate	13
generate.bru	15
gg	16
gg.data.frame	17
gg.inla.mesh	19
gg.inla.mesh.1d	20
gg.matrix	22
gg.prediction	22
gg.RasterLayer	24
gg.SpatialGridDataFrame	25
gg.SpatialLines	27
gg.SpatialPixels	28
gg.SpatialPixelsDataFrame	29
gg.SpatialPoints	31
gg.SpatialPolygons	32
globe	34
gplot	35
gplot.inla.mesh	36
gplot.SpatialLines	37
gplot.SpatialPoints	38
gm	39
gmap	40
gorillas	41
init.tutorial	43
inlabru	43
int	44
ipoints	45
lgcp	47
like	48
mexdolphins	50
mrsea	51
multiplot	52
pixels	53
plot.bru	54
plot.prediction	55
plotsample	56
point2count	58
Poisson1_1D	58
Poisson2_1D	59

Poisson3_1D 60

predict.bru 62

predict.inla 64

sample.lgcp 66

seals 67

sline 68

spatial.to.ppp 69

spde.posterior 70

spoly 71

stransform 72

summary.bru 73

toygroups 74

vertices 75

vertices.inla.mesh 76

Index 77

bincount *1D LGCP bin count simulation and comparison with data*

Description

A common procedure of analyzing the distribution of 1D points is to chose a binning and plot the data's histogram with respect to this binning. This function compares the counts that the histogram calculates to simulations from a 1D log Gaussian Cox process conditioned on the number of data samples. For each bin this results in a median number of counts as well as a confidence interval. If the LGCP is a plausible model for the observed points then most of the histogram counts (number of points within a bin) should be within the confidence intervals. Note that a proper comparison is a multiple testing problem which the function does not solve for you.

Usage

```
bincount(result, predictor, observations, breaks, nint = 20,
         probs = c(0.025, 0.5, 0.975), ...)
```

Arguments

- result A result object from a [bru](#) or [lgcp](#) call
- predictor A formula describing the prediction of a 1D LGCP via [predict](#).
- observations A vector of observed values
- breaks A vector of bin boundaries
- nint Number of integration points per bin. Increase this if the bins are wide and
- probs numeric vector of probabilities with values in [0,1]
- ... arguments passed on to [predict](#)

Value

An [inla](#) object

Examples

```
## Not run:

# Load a point pattern
data(Poisson2_1D)

# Take a look at the point (and frequency) data

ggplot(pts2) +
  geom_histogram(aes(x = x), binwidth = 55/20, boundary = 0, fill = NA, color = "black") +
  geom_point(aes(x), y = 0, pch = "|", cex = 4) +
  coord_fixed(ratio = 1)

#' Fit an LGCP model
x <- seq(0, 55, length = 50)
mesh1D <- inla.mesh.1d(x, boundary = "free")
mdl <- x ~ spde1D(map = x, model = inla.spde2.matern(mesh1D)) + Intercept # SOLUTION
init.tutorial()
fit.spde <- lgcp(mdl, pts2, domain = list(x = c(0,55)))

# Calculate bin statistics
bc <- bincount(result = fit.spde,
              observations = pts2,
              breaks = seq(0,max(pts2),length = 12),
              predictor = x ~ exp(spde1D + Intercept))

# Plot them!
attributes(bc)$ggp

## End(Not run)
```

bru

Convenient model fitting using (iterated) INLA

Description

This method is a wrapper for [inla](#) and provides multiple enhancements.

- Easy usage of spatial covariates and automatic construction of inla projection matrices for (spatial) SPDE models. This feature is accessible via the `components` parameter. Practical examples on how to use spatial data by means of the `components` parameter can also be found by looking at the [lgcp](#) function's documentation.

- Constructing multiple likelihoods is straight forward. See [like](#) for more information on how to provide additional likelihoods to bru using the ... parameter list.
- Support for non-linear predictors. See example below.
- Log Gaussian Cox process (LGCP) inference is available by using the cp family or (even easier) by using the [lgcp](#) function.

Usage

```
bru(components = y ~ Intercept, family = NULL, data = NULL, ...,
     options = list())
```

Arguments

components	a formula describing the latent components. See bru.components for details.
family	A string indicating the likelihood family. The default is gaussian with identity link. In addition to the likelihoods provided by inla (see <code>inla.models()\$likelihood</code>) inlabru supports fitting Cox processes via <code>family = "cp"</code> . The latter requires constructing a likelihood using the like function and providing it via the ... parameter list. As an alternative to bru, the lgcp function provides a convenient interface to fitting Cox processes.
data	A data.frame or SpatialPoints[DataFrame] object.
...	Additional likelihoods, each constructed by a calling like .
options	A list of name and value pairs that are either interpretable by bru.options or valid inla parameters.

Value

bru returns an object of class "bru". A bru object inherits from [inla](#) (see the inla documentation for its properties) and adds additional information stored in the `sppa` field.

Author(s)

Fabian E. Bachl <<bachlfab@gmail.com>>

Examples

```
# Simulate some covariates x and observations y
input.df <- data.frame(x=cos(1:10))
input.df <- within(input.df, y <- 5 + 2*x + rnorm(10, mean=0, sd=0.1))

# Fit a Gaussian likelihood model
fit <- bru(y ~ x + Intercept, "gaussian", input.df)

# Obtain summary
summary(fit)

# Alternatively, we can use the like() function to construct the likelihood:
```

```
lik = like(family = "gaussian", data = input.df)
fit <- bru(y ~ x + Intercept, lik)
summary(fit)

# An important addition to the INLA methodology is bru's ability to use
# non-linear predictors. Such a predictor can be formulated via like()'s
# \code{formula} parameter. For instance

z = 2
input.df <- within(input.df, y <- 5 + exp(z)*x + rnorm(10, mean=0, sd=0.1))
lik = like(family = "gaussian", data = input.df, formula = y ~ exp(z)*x + Intercept, E = 10000)
fit <- bru(~ z + Intercept, lik)

# Check the result (z posterior should be around 2)
summary(fit)
```

bru.components

bru components

Description

Similar to `glm()`, `gam()` and `inla()` `bru` uses formula objects to describe response data and latent (unknown) components of the model to be fitted. However, in addition to the syntax compatible with `inla`, `bru` components offer additional functionality which facilitates modeling.

Usage

```
bru.components()
```

Details

`bru` will understand formulae describing fixed effect models just like the other methods. For instance, the formula `y ~ x` will fit the linear combination of an effect named `x` and an intercept to the response `y` with respect to the likelihood family stated when calling `bru`. Mathematically, the linear predictor η would be written down as

$$\eta = \beta * x + c,$$

where:

- c is the *intercept*
- x is a *covariate*
- β is a *random variable* associated with x and
- $\psi = \beta * x$ is called the *random effect* of x

A problem that arises when using this kind of R formula is that it does not clearly select the mathematical formula. For instance, when providing the formula to `inla`, the resulting object will refer to the random effect $\psi = \beta * x$ as `x`. Hence, it is not clear if `x` refers to the covariate or the effect of the covariate.

Naming random effects

In inla, a simple random effect model would be expressed as

- `formula = y ~ f(x, model = "linear"),`

where `f` is the inla specific function to set up random effects of all kinds. The underlying predictor would again be $\eta = \beta * x + c$ but the result of fitting the model would state `x` as the random effect's name. `bru` allows to rewrite this formula in order to explicitly state the name of the random effect and the name of the associated. This is achieved by replacing `f` with an arbitrary name that we wish to assign to the effect, e.g.

- `components = y ~ psi(x, model = "linear").`

Being able to discriminate between x and ψ is relevant because of two functionalities `bru` offers. The formula parameters of both, `bru` and the prediction method `predict.bru` are interpreted in the mathematical sense. For instance, `predict` may be used to analyze the an analytical combination of the covariate x and the intercept using

- `predict(fit, data.frame(x=1)), ~ exp(x + Intercept).`

On the other hand, `predict` may be used to only look at a transformation of the random effect ψ

- `predict(fit, NULL, ~ exp(psi).`

Simple covariates and the map parameter

It is not unusual for a random effect act on a transformation of a covariate. In other frameworks this would mean that the transformed covariate would have to be calculated in advance and added to the data frame that is usually provided via the `data` parameter. `inlabru` provides the option to do this transformation automatically. For instance, one might be interested in the effect of a covariate x^2 . In inla and other frameworks this would require to add a column `xsquared` to the input data frame and use the formula

- `formula = y ~ f(xsquared, model = "linear"),`

In `inlabru` this can be achieved using two ways of using the `map` parameter.

- `components = y ~ psi(map = x^2, model = "linear")`
- `components = y ~ psi(map = mySquareFun(x), model = "linear"),`
- `components = y ~ psi(map = myOtherSquareFun, model = "linear"),`

In the first example `inlabru` will interpret the `map` parameter as an expression to be evaluated within the data provided. Since x is a known covariate it will know how to calculate it. The second example is an expression as well but it uses a function called `mySquareFun`. This function is defined by user but has to be accessible within the work space when setting up the components. The third example provides the function `myOtherSquareFun` directly and not within an expression. In this case, `inlabru` will call the function using the data provided via the `data` parameter. `inlabru` expects that the output of this function is a data.frame with "psi" being the name of the single existing column. For instance,

```
myOtherSquareFun = function(data) {
  colnames(data) = "psi" ;
  data = data[, "x", drop = FALSE] ;
  return(data)}
```

Spatial Covariates

When fitting spatial models it is common to work with covariates that depend on space, e.g. sea surface temperature or elevation. Although it is straight forward to add this data to the input data frame or write a covariate function like in the previous section there is an even more convenient way in inlabru. Spatial covariates are often stored as `SpatialPixelDataFrame`, `SpatialPixelDataFrame` or `RasterLayer` objects. These can be provided directly via the `map` parameter if the input data is a `SpatialPointsDataFrame`. inlabru will automatically evaluate and/or interpolate the covariate at your data locations when using code like

- `components = y ~ psi(mySpatialPixels, model = "linear")`.

Coordinates

A common spatial modelling component when using inla are SPDE models. An important feature of inlabru is that it will automatically calculate the so called A-matrix which maps SPDE values at the mesh vertices to values at the data locations. For this purpose, the `map` parameter can be set to `coordinates`, which is the `sp` package function that extracts point coordinates from the `SpatialPointsDataFrame` that was provided as input to `bru`. The code for this would look as follows:

- `components = y ~ mySPDE(map = coordinates, model = inla.spde2.matern(...))`.

Author(s)

Fabian E. Bachl <<bachlfab@gmail.com>>

bru.options

Additional [bru](#) options

Description

Additional [bru](#) options

Usage

```
bru.options(mesh = NULL, run = TRUE, max.iter = 10, offset = 0,
  result = NULL, E = 1, control.compute = list(config = TRUE, dic = TRUE,
  waic = TRUE), control.inla = iinla.getOption("control.inla"), ...)
```

Arguments

<code>mesh</code>	An <code>inla.mesh</code> object for spatial models without SPDE components. Mostly used for successive spatial predictions.
<code>run</code>	If <code>TRUE</code> , run inference. Otherwise only return configuration needed to run inference.
<code>max.iter</code>	maximum number of inla iterations
<code>offset</code>	the usual inla offset. If a nonlinear formula is used, the resulting Taylor approximation constant will be added to this automatically.

result An inla object returned from previous calls of [inla](#), [bru](#) or [lgcp](#). This will be used as a starting point for further improvement of the approximate posterior.

E [inla](#) exposure parameter

control.compute INLA option, See [control.compute](#)

control.inla INLA option, See [control.inla](#)

... Additional options passed on to [inla](#)

Author(s)

Fabian E. Bachl <<bachlfab@gmail.com>>

Examples

```
## Not run:

# Generate default bru options
opts = bru.options()

# Print them:
opts

## End(Not run)
```

cprod

Cross product of integration points

Description

Calculates the cross product of integration points in different dimensions and multiplies their weights accordingly. If the object defining points in a particular dimension has no weights attached to it all weights are assumed to be 1.

Usage

```
cprod(...)
```

Arguments

... data.frame or SpatialPointsDataFrame objects, each one usually obtained by a call to the [ipoints](#) function.

Value

A data.frame or SpatialPointsDataFrame of multidimensional integration points and their weights

Author(s)

Fabian E. Bachl <<bachlfab@gmail.com>>

Examples

```
# Create integration points in dimension 'myDim' and 'myDiscreteDim'
ips1 = ipoints(c(0,8), name = "myDim")
ips2 = ipoints(as.integer(c(1,2,3)), name = "myDiscreteDim")

# Calculate the cross product
ips = cprod(ips1, ips2)

# Plot the integration points
plot(ips$myDim, ips$myDiscreteDim, cex = 10*ips$weight)
```

deltaIC

Summarise DIC and WAIC from lgcp objects.

Description

Calculates DIC and WAIC differences and produces an ordered summary.

Usage

```
deltaIC(..., criterion = "DIC")
```

Arguments

... Comma-separated objects inheriting from class `inla` and obtained from a run of [inla](#), [bru](#) or [lgcp](#)

criterion If 'DIC', plots DIC differences; If 'WAIC', plots WAIC differences.

Value

A data frame with each row containing the model name, DIC, WAIC, deltaDIC, and deltaWAIC.

Examples

```
# Generate some data
input.df <- data.frame(x=cos(1:10))
input.df <- within(input.df, y <- 5 + 2*cos(1:10) + rnorm(10, mean=0, sd=0.1))

# Fit two models
fit <- bru(y ~ x, "gaussian", input.df)
```

```
fit2 <- bru(y ~ x, "Poisson", input.df)

# Compare DIC

deltaIC(fit, fit2)
```

devel.cvmeasure	<i>Variance and correlations measures for prediction components</i>
-----------------	---

Description

Calculates local and integrated variance and correlation measures as introduced by Yuan et al. (2017).

Usage

```
devel.cvmeasure(joint, prediction1, prediction2, samplers = NULL,
  mesh = NULL)
```

Arguments

joint	A joint prediction of two latent model components.
prediction1	A prediction of first component.
prediction2	A prediction of the first component.
samplers	A SpatialPolygon object describing the area for which to compute the cumulative variance measure.
mesh	The inla.mesh for which the prediction was performed (required for cumulative Vmeasure).

Value

Variance and correlations measures.

References

Y. Yuan, F. E. Bachl, F. Lindgren, D. L. Brochers, J. B. Illian, S. T. Buckland, H. Rue, T. Gerrodette. 2017. Point process models for spatio-temporal distance sampling data from a large-scale survey of blue whales. <https://arxiv.org/abs/1604.06013>

Examples

```

## Not run:
# Load Gorilla data

data("gorillas")

# Use RColorBrewer

library(RColorBrewer)

# Fit a model with two components:
# 1) A spatial smooth SPDE
# 2) A spatial covariate effect (vegetation)

pcmatern <- inla.spde2.pcmatern(gorillas$mesh,
                              prior.sigma = c(0.1, 0.01),
                              prior.range = c(5, 0.01))

cmp <- coordinates ~ vegetation(map = gorillas$gcov$vegetation, model = "factor") +
  spde(map = coordinates, model = pcmatern, mesh = gorillas$mesh) -
  Intercept

init.tutorial() # Faster inference for example

fit <- lgcp(cmp, gorillas$mesh, samplers = gorillas$boundary)

# Predict SPDE and vegetation at the mesh vertex locations

vrt = vertices(gorillas$mesh)
joint <- predict(fit, vrt, ~ spde + vegetation)
field <- predict(fit, vrt, ~ spde)
veg <- predict(fit, vrt, ~ vegetation)

# Plot component mean

multiplot(ggplot() + gg(gorillas$mesh, color = joint$mean) +
  coord_equal() + theme(legend.position = "bottom"),
  ggplot() + gg(gorillas$mesh, color = field$mean) +
  coord_equal() + theme(legend.position = "bottom"),
  ggplot() + gg(gorillas$mesh, color = veg$mean) +
  coord_equal() + theme(legend.position = "bottom"),
  cols = 3)

# Plot component variance

multiplot(ggplot() + gg(gorillas$mesh, color = joint$var) +
  coord_equal() + theme(legend.position = "bottom"),
  ggplot() + gg(gorillas$mesh, color = field$var) +
  coord_equal() + theme(legend.position = "bottom"),
  ggplot() + gg(gorillas$mesh, color = veg$var) +
  coord_equal() + theme(legend.position = "bottom"),
  cols = 3)

```

```

# Calculate variance and correlation measure

vm <- devel.cvmeasure(joint, field, veg)
lprange <- range(vm$var.joint, vm$var1, vm$var2)

# Variance contribution of the components

csc <- scale_fill_gradientn(colours = brewer.pal(9, "YlOrRd"), limits = lprange)
boundary <- gorillas$boundary

plot.1 <- ggplot() + gg(gorillas$mesh, color = vm$var.joint, mask = boundary) +
  csc + coord_equal() + ggtitle("joint") + theme(legend.position = "bottom")
plot.2 <- ggplot() + gg(gorillas$mesh, color = vm$var1, mask = boundary) +
  csc + coord_equal() + ggtitle("SPDE") + theme(legend.position = "bottom")
plot.3 <- ggplot() + gg(gorillas$mesh, color = vm$var2, mask = boundary) +
  csc + coord_equal() + ggtitle("vegetation") + theme(legend.position = "bottom")

multiplot(plot.1, plot.2, plot.3, cols = 3)

# Covariance of SPDE field and vegetation

ggplot() + gg(gorillas$mesh, color = vm$cov)

# Correlation between field and vegetation

ggplot() + gg(gorillas$mesh, color = vm$cor)

# Variance and correlation integrated over space

vm.int <- devel.cvmeasure(joint, field, veg,
  samplers = ipoints(gorillas$boundary, gorillas$mesh),
  mesh = gorillas$mesh)

vm.int

## End(Not run)

```

generate

Generate samples from fitted bru and inla models

Description

Generic function for sampling for fitted models. The function invokes particular methods which depend on the class of the first argument.

Usage

```
generate(object, ...)
```

Arguments

object a fitted model.
 ... additional arguments affecting the samples produced.

Value

The form of the value returned by `gg` depends on the class of its argument. See the documentation of the particular methods for details of what is produced by that method.

See Also

Other sample generators: [generate.bru](#)

Examples

```
# Generate data for a simple linear model

input.df <- data.frame(x=cos(1:10))
input.df <- within(input.df, y <- 5 + 2*cos(1:10) + rnorm(10, mean=0, sd=0.1))

# Fit the model

fit <- bru(y ~ xeff(map = x, model = "linear"), "gaussian", input.df)
summary(fit)

# Generate samples for some predefined x

df = data.frame(x = seq(-4, 4, by = 0.1))
smp = generate(fit, df, ~ xeff + Intercept, n.samples = 10)

# Plot the resulting realizations

plot(df$x, smp[[1]], type = "l")
for (k in 2:length(smp)) points(df$x, smp[[k]], type = "l")

# We can also draw samples form the joint posterior

df = data.frame(x = 1)
smp = generate(fit, df, ~ data.frame(xeff, Intercept), n.samples = 10)
smp[[1]]

# ... and plot them

plot(do.call(rbind, smp))
```

generate.bru

*Sampling based on bru posteriors***Description**

Takes a fitted bru object produced by the function `bru()` and produces samples given a new set of values for the model covariates or the original values used for the model fit. The samples can be based on any R expression that is valid given these values/covariates and the joint posterior of the estimated random effects.

Mean value predictions are accompanied by the standard errors, upper and lower 2.5 median, variance, coefficient of variation as well as the variance and minimum and maximum sample value drawn in course of estimating the statistics.

Usage

```
## S3 method for class 'bru'
generate(object, data, formula = NULL, n.samples = 100, ...)
```

Arguments

<code>object</code>	A bru object obtained by calling <code>bru</code> .
<code>data</code>	A data.frame or SpatialPointsDataFrame of covariates needed for sampling.
<code>formula</code>	A formula determining which effects to sample from and how to combine them analytically.
<code>n.samples</code>	Integer setting the number of samples to draw in order to calculate the posterior statistics. The default is rather low but provides a quick approximate result.
<code>...</code>	ignored arguments (needed for S3 compatibility).

Value

Predicted values

See Also

Other sample generators: [generate](#)

Examples

```
# Generate data for a simple linear model

input.df <- data.frame(x=cos(1:10))
input.df <- within(input.df, y <- 5 + 2*cos(1:10) + rnorm(10, mean=0, sd=0.1))

# Fit the model

fit <- bru(y ~ xeff(map = x, model = "linear"), "gaussian", input.df)
```

```
summary(fit)

# Generate samples for some predefined x

df = data.frame(x = seq(-4, 4, by = 0.1))
smp = generate(fit, df, ~ xeff + Intercept, n.samples = 10)

# Plot the resulting realizations

plot(df$x, smp[[1]], type = "l")
for (k in 2:length(smp)) points(df$x, smp[[k]], type = "l")

# We can also draw samples form the joint posterior

df = data.frame(x = 1)
smp = generate(fit, df, ~ data.frame(xeff, Intercept), n.samples = 10)
smp[[1]]

# ... and plot them

plot(do.call(rbind, smp))
```

gg

ggplot2 geomes for inlabru related objects

Description

gg is a generic function for generating geomes from various kinds of spatial objects, e.g. Spatial* data, meshes, Raster objects and inla/inlabru predictions. The function invokes particular methods which depend on the [class](#) of the first argument.

Usage

```
gg(data, ...)
```

Arguments

data	an object for which to generate a geom.
...	Arguments passed on to the geom method.

Value

The form of the value returned by gg depends on the class of its argument. See the documentation of the particular methods for details of what is produced by that method.

See Also

Other geomes for inla and inlabru predictions: [gg.data.frame](#), [gg.matrix](#), [gg.prediction](#), [gm](#)

Other geomes for spatial data: [gg.SpatialGridDataFrame](#), [gg.SpatialLines](#), [gg.SpatialPixelsDataFrame](#), [gg.SpatialPixels](#), [gg.SpatialPoints](#), [gg.SpatialPolygons](#), [gm](#)

Other geomes for meshes: [gg.inla.mesh.1d](#), [gg.inla.mesh](#), [gm](#)

Other geomes for Raster data: [gg.RasterLayer](#), [gm](#)

Examples

```
# Load Gorilla data
data(gorillas)

# Invoke ggplot and add geomes for the Gorilla nests and the survey boundary
ggplot() + gg(gorillas$boundary) + gg(gorillas$nests)
```

gg.data.frame

Geom for data.frame

Description

This geom constructor will simply call [gg.prediction](#) for the data provided.

Usage

```
## S3 method for class 'data.frame'
gg(...)
```

Arguments

... Arguments passed on to [gg.prediction](#).

Value

Concatenation of a [geom_line](#) value and optionally a [geom_ribbon](#) value.

See Also

Other geomes for inla and inlabru predictions: [gg.matrix](#), [gg.prediction](#), [gg](#), [gm](#)

Examples

```

# Generate some data

input.df <- data.frame(x=cos(1:10))
input.df <- within(input.df, y <- 5 + 2*cos(1:10) + rnorm(10, mean=0, sd=0.1))

# Fit a model with fixed effect 'x' and intercept 'Intercept'

fit <- bru(y ~ x, "gaussian", input.df)

# Predict posterior statistics of 'x'

xpost = predict(fit, formula = ~ x)

# The statistics include mean, standard deviation, the 2.5% quantile, the median,
# the 97.5% quantile, minimum and maximum sample drawn from the posterior as well as
# the coefficient of variation and the variance.

xpost

# For a single variable like 'x' the default plotting method invoked by gg() will
# show these statistics in a fashion similar to a box plot:
ggplot() + gg(xpost)

# The predict function can also be used to simulatenneously estimate posteriors
# of multiple variables:

xipost = predict(fit, formula = ~ data.frame(post = c(Intercept, x)))
xipost

# If we still want a plot in the previous style we have to set the bar parameter to TRUE

rownames(xipost) = c("Intercept", "x")
p1 = ggplot() + gg(xipost, bar = TRUE)
p1

# Note that gg also understands the posterior estimates generated while running INLA

p2 = ggplot() + gg(fit$summary.fixed, bar = TRUE)
multiplot(p1, p2)

# By default, if the prediction has more than one row, gg will plot the column 'mean' against
# the row index. This is for instance usefuul for predicting and plotting function
# but not very meaningful given the above example:

ggplot() + gg(xipost)

# For ease of use we can also type

plot(xipost)

```

```
# This type of plot will show a ribbon around the mean, which visualizes the upper and lower
# quantiles mentioned above (2.5 and 97.5%). Plotting the ribbon can be turned of using the
# \code{ribbon} parameter

ggplot() + gg(xipost, ribbon = FALSE)

# Much like the other geomes produced by gg we can adjust the plot using ggplot2 style
# commands, for instance

ggplot() +
  gg(xipost) +
  gg(xipost, mapping = aes(y = median), ribbon = FALSE, color = "red")
```

 gg.inla.mesh

Geom for inla.mesh objects

Description

This function extracts the graph of an `inla.mesh` object and uses `geom_line` to visualize the graph's edges. Alternatively, if the `color` argument is provided, interpolates the colors across for a set of `SpatialPixels` covering the mesh area and calls `gg.SpatialPixelDataFrame()` to plot the interpolation.

Usage

```
## S3 method for class 'inla.mesh'
gg(data, color = NULL, alpha = NULL,
  edge.color = "grey", interior = TRUE, int.color = "blue",
  exterior = TRUE, ext.color = "black", crs = NULL, mask = NULL,
  nx = 500, ny = 500, ...)
```

Arguments

<code>data</code>	An <code>inla.mesh</code> object.
<code>color</code>	A vector of scalar values to fill the mesh with colors. The length of the vector must correspond to the number of mesh vertices.
<code>alpha</code>	A vector of scalar values setting the alpha value of the colors provided.
<code>edge.color</code>	Color of the mesh edges.
<code>interior</code>	If TRUE, plot the interior boundaries of the mesh.
<code>int.color</code>	Color used to plot the interior boundaries.
<code>exterior</code>	If TRUE, plot the exterior boundaries of the mesh.
<code>ext.color</code>	Color used to plot the interior boundaries.
<code>crs</code>	A <code>CRS</code> object defining the coordinate system to project the mesh to before plotting.

mask	A SpatialPolygon defining the region that is plotted.
nx	Number of pixels in x direction (when plotting using the color parameter).
ny	Number of pixels in y direction (when plotting using the color parameter).
...	ignored arguments (S3 generic compatibility).

Value

`geom_line` return values or, if the color argument is used, the values of `gg.SpatialPixelDataFrame()`.

See Also

Other geomes for meshes: [gg.inla.mesh.1d](#), [gg](#), [gm](#)

Examples

```
# Load Gorilla data
data("gorillas")

# Plot mesh using default edge colors

ggplot() + gg(gorillas$mesh)

# Don't show interior and exterior boundaries

ggplot() + gg(gorillas$mesh, interior = FALSE, exterior = FALSE)

# Change the edge colors

ggplot() + gg(gorillas$mesh,
              edge.color = "green",
              int.color = "black",
              ext.color = "blue"
              )

# Use the x-coordinate of the vertices to colorize the triangles and
# mask the plotted area by the survey boundary, i.e. only plot the inside

xcoord = gorillas$mesh$loc[,1]
ggplot() +
  gg(gorillas$mesh, color = (xcoord-580), mask = gorillas$boundary) +
  gg(gorillas$boundary)
```

Description

This function generates a [geom_point](#) object showing the knots (vertices) of a 1D mesh.

Usage

```
## S3 method for class 'inla.mesh.1d'  
gg(data, mapping = aes_string("x", "y"), y = 0,  
    shape = 4, ...)
```

Arguments

data	An inla.mesh.1d object.
mapping	aesthetic mappings created by aes or aes_ . These are passed on to geom_point .
y	Single or vector numeric defining the y-coordinates of the mesh knots to plot.
shape	Shape of the knot markers.
...	parameters passed on to geom_point .

Value

An object generated by [geom_point](#).

See Also

Other geomes for meshes: [gg.inla.mesh](#), [gg](#), [gm](#)

Examples

```
# Load INLA  
library(INLA)  
  
# Create a 1D mesh  
mesh = inla.mesh.1d(seq(0,10,by=0.5))  
  
# Plot it  
ggplot() + gg(mesh)  
  
# Plot it using a different shape and size for the mesh nodes  
ggplot() + gg(mesh, shape = "|", size = 5)
```

gg.matrix	<i>Geom for matrix</i>
-----------	------------------------

Description

Creates a tile geom for plotting a matrix

Usage

```
## S3 method for class 'matrix'
gg(data, mapping = NULL, ...)
```

Arguments

data	A matrix object.
mapping	a set of aesthetic mappings created by aes or aes_ . These are passed on to geom_tile .
...	Arguments passed on to geom_tile .

Value

A [geom_tile](#) with reversed y scale.

See Also

Other geomes for inla and inlabru predictions: [gg.data.frame](#), [gg.prediction](#), [gg](#), [gm](#)

Examples

```
A = matrix(runif(100), nrow = 10)
ggplot() + gg(A)
```

gg.prediction	<i>Geom for predictions</i>
---------------	-----------------------------

Description

This geom serves to visualize prediction objects which usually results from a call to [predict.bru](#). Predictions objects provide summary statistics (mean, median, sd, ...) for one or more random variables. For single variables (or if requested so by setting `bar = TRUE`), a boxplot-style geom is constructed to show the statistics. For multivariate predictions the mean of each variable (y-axis) is plotted against the row number of the variable in the prediction data frame (x-axis) using [geom_line](#). In addition, a [geom_ribbon](#) is used to show the confidence interval.

Note: `gg.prediction` also understands the format of INLA-style posterior summaries, e.g. `fit$summary.fixed` for an inla object `fit`

Usage

```
## S3 method for class 'prediction'
gg(data, mapping = NULL, ribbon = TRUE, alpha = 0.3,
    bar = FALSE, ...)
```

Arguments

data	A prediction object, usually the result of a predict.bru call.
mapping	a set of aesthetic mappings created by aes or aes_ . These are passed on to geom_line .
ribbon	If TRUE, plot a ribbon around the line based on the upper and lower 2.5 percent quantiles.
alpha	The ribbons numeric alpha level in [0,1].
bar	If TRUE plot boxplot-style summary for each variable.
...	Arguments passed on to geom_line .

Value

Concatenation of a [geom_line](#) value and optionally a [geom_ribbon](#) value.

See Also

Other geomes for inla and inlabru predictions: [gg.data.frame](#), [gg.matrix](#), [gg.gm](#)

Examples

```
# Generate some data

input.df <- data.frame(x=cos(1:10))
input.df <- within(input.df, y <- 5 + 2*cos(1:10) + rnorm(10, mean=0, sd=0.1))

# Fit a model with fixed effect 'x' and intercept 'Intercept'

fit <- bru(y ~ x, "gaussian", input.df)

# Predict posterior statistics of 'x'

xpost = predict(fit, formula = ~ x)

# The statistics include mean, standard deviation, the 2.5% quantile, the median,
# the 97.5% quantile, minimum and maximum sample drawn from the posterior as well as
# the coefficient of variation and the variance.

xpost

# For a single variable like 'x' the default plotting method invoked by gg() will
# show these statistics in a fashion similar to a box plot:
ggplot() + gg(xpost)
```

```

# The predict function can also be used to simulatenneously estimate posteriors
# of multiple variables:

xipost = predict(fit, formula = ~ data.frame(post = c(Intercept, x)))
xipost

# If we still want a plot in the previous style we have to set the bar parameter to TRUE

rownames(xipost) = c("Intercept", "x")
p1 = ggplot() + gg(xipost, bar = TRUE)
p1

# Note that gg also understands the posterior estimates generated while running INLA

p2 = ggplot() + gg(fit$summary.fixed, bar = TRUE)
multiplot(p1, p2)

# By default, if the prediction has more than one row, gg will plot the column 'mean' against
# the row index. This is for instance usefuul for predicting and plotting function
# but not very meaningful given the above example:

ggplot() + gg(xipost)

# For ease of use we can also type

plot(xipost)

# This type of plot will show a ribbon around the mean, which viszualizes the upper and lower
# quantiles mentioned above (2.5 and 97.5%). Plotting the ribbon can be turned of using the
# \code{ribbon} parameter

ggplot() + gg(xipost, ribbon = FALSE)

# Much like the other geomes produced by gg we can adjust the plot using ggplot2 style
# commands, for instance

ggplot() +
  gg(xipost) +
  gg(xipost, mapping = aes(y = median), ribbon = FALSE, color = "red")

```

gg.RasterLayer

Geom for RasterLayer objects

Description

This function takes a RasterLayer object, converts it into a SpatialPixelsDataFrame and uses [geom_tile](#) to plot the data.

Usage

```
## S3 method for class 'RasterLayer'
gg(data, mapping = aes_string(x = "x", y = "y", fill =
  "layer"), ...)
```

Arguments

data	A RasterLayer object.
mapping	aesthetic mappings created by aes or aes_ . These are passed on to geom_tile .
...	Arguments passed on to geom_tile .

Value

An object returned by [geom_tile](#)

See Also

Other geomes for Raster data: [gg](#), [gm](#)

Examples

```
# Load Gorilla data
data("gorillas", package = "spatstat.data")

# Convert elevation covariate to RasterLayer

library(raster)
elev = as(gorillas.extra$elevation, "RasterLayer")

# Plot the elevation

ggplot() + gg(elev)
```

```
gg.SpatialGridDataFrame
```

Geom for SpatialGridDataFrame objects

Description

Coerces input SpatialGridDataFrame to SpatialPixelsDataFrame and calls gg.SpatialPixelDataFrame to plot it.

Usage

```
## S3 method for class 'SpatialGridDataFrame'
gg(data, ...)
```

Arguments

`data` A `SpatialGridDataFrame` object.
`...` Arguments passed on to `gg.SpatialPixelsDataFrame()`.

Value

A `geom_tile` value.

See Also

Other geomes for spatial data: [gg.SpatialLines](#), [gg.SpatialPixelsDataFrame](#), [gg.SpatialPixels](#), [gg.SpatialPoints](#), [gg.SpatialPolygons](#), [gg.gm](#)

Examples

```
# Load Gorilla data
data("gorillas")

# Plot Gorilla elevation covariate provided as SpatialPixelsDataFrame.
# The same syntax applies to SpatialGridDataFrame objects.

ggplot() + gg(gorillas$gcov$elevation)

# Add Gorilla survey boundary and nest sightings

ggplot() +
  gg(gorillas$gcov$elevation) +
  gg(gorillas$boundary) +
  gg(gorillas$nests)

# Load pantropical dolphin data
data("mexdolphins")

# Plot the pantropical survey boundary, ship transects and dolphin sightings

ggplot() +
  gg(mexdolphins$ppoly) + # survey boundary as SpatialPolygon
  gg(mexdolphins$samplers) + # ship transects as SpatialLines
  gg(mexdolphins$points) # dolphin sightings as SpatialPoints

# Change color

ggplot() +
  gg(mexdolphins$ppoly, color = "green") + # survey boundary as SpatialPolygon
  gg(mexdolphins$samplers, color = "red") + # ship transects as SpatialLines
  gg(mexdolphins$points, color = "blue") # dolphin sightings as SpatialPoints
```

```

# Visualize data annotations: line width by segment number

names(mexdolphinsamplers) # 'seg' holds the segment number
ggplot() + gg(mexdolphinsamplers, aes(color = seg))

# Visualize data annotations: point size by dolphin group size

names(mexdolphinspoints) # 'size' holds the group size
ggplot() + gg(mexdolphinspoints, aes(size = size))

```

gg.SpatialLines *Geom for SpatialLines objects*

Description

Extracts start and end points of the lines and calls [geom_segment](#) to plot lines between them.

Usage

```

## S3 method for class 'SpatialLines'
gg(data, mapping = NULL, crs = NULL, ...)

```

Arguments

data	A SpatialLines object.
mapping	Aesthetic mappings created by aes or aes_ used to update the default mapping. The default mapping is <code>aes_string(x = coordnames(data)[1], y = coordnames(data)[2], xend = p</code>
crs	A CRS object defining the coordinate system to project the data to before plotting.
...	Arguments passed on to geom_segment .

Value

A [geom_segment](#) return value.

See Also

Other geomes for spatial data: [gg.SpatialGridDataFrame](#), [gg.SpatialPixelsDataFrame](#), [gg.SpatialPixels](#), [gg.SpatialPoints](#), [gg.SpatialPolygons](#), [gg, gm](#)

Examples

```

# Load Gorilla data

data("gorillas")

# Plot Gorilla elevation covariate provided as SpatialPixelsDataFrame.
# The same syntax applies to SpatialGridDataFrame objects.

ggplot() + gg(gorillas$gcov$elevation)

# Add Gorilla survey boundary and nest sightings

ggplot() +
  gg(gorillas$gcov$elevation) +
  gg(gorillas$boundary) +
  gg(gorillas$nest)

# Load pantropical dolphin data

data("mexdolphins")

# Plot the pantropical survey boundary, ship transects and dolphin sightings

ggplot() +
  gg(mexdolphins$poly) + # survey boundary as SpatialPolygon
  gg(mexdolphins$samplers) + # ship transects as SpatialLines
  gg(mexdolphins$points) # dolphin sightings as SpatialPoints

# Change color

ggplot() +
  gg(mexdolphins$poly, color = "green") + # survey boundary as SpatialPolygon
  gg(mexdolphins$samplers, color = "red") + # ship transects as SpatialLines
  gg(mexdolphins$points, color = "blue") # dolphin sightings as SpatialPoints

# Visualize data annotations: line width by segment number

names(mexdolphins$samplers) # 'seg' holds the segment number
ggplot() + gg(mexdolphins$samplers, aes(color = seg))

# Visualize data annotations: point size by dolphin group size

names(mexdolphins$points) # 'size' holds the group size
ggplot() + gg(mexdolphins$points, aes(size = size))

```

Description

Uses [geom_point](#) to plot the pixel centers.

Usage

```
## S3 method for class 'SpatialPixels'
gg(data, ...)
```

Arguments

data A [SpatialPixels](#) object.
... Arguments passed on to [geom_tile](#).

Value

A [geom_tile](#) return value.

See Also

Other geomes for spatial data: [gg.SpatialGridDataFrame](#), [gg.SpatialLines](#), [gg.SpatialPixelsDataFrame](#), [gg.SpatialPoints](#), [gg.SpatialPolygons](#), [gg, gm](#)

Examples

```
# Load Gorilla data

data(gorillas)

# Turn elevation covariate into SpatialPixels
pxl = SpatialPixels(SpatialPoints(gorillas$gcov$elevation))

# Plot the pixel centers
ggplot() + gg(pxl, size = 0.1)
```

```
gg.SpatialPixelsDataFrame
```

Geom for SpatialPixelsDataFrame objects

Description

Coerces input [SpatialPixelsDataFrame](#) to `data.frame` and uses [geom_tile](#) to plot it.

Usage

```
## S3 method for class 'SpatialPixelsDataFrame'
gg(data, mapping = NULL, alpha = NULL,
    crs = NULL, mask = NULL, ...)
```

Arguments

<code>data</code>	A <code>SpatialPixelsDataFrame</code> object.
<code>mapping</code>	Aesthetic mappings created by <code>aes</code> or <code>aes_</code> used to update the default mapping. The default mapping is <code>aes_string(x = coordnames(data)[1], y = coordnames(data)[2], fill =</code>
<code>alpha</code>	Character array identifying the data column used for tile transparency.
<code>crs</code>	A CRS object defining the coordinate system to project the data to before plotting.
<code>mask</code>	A <code>SpatialPolygon</code> defining the region that is plotted.
<code>...</code>	Arguments passed on to <code>geom_tile</code> .

Value

A `geom_tile` return value.

See Also

Other geomes for spatial data: [gg.SpatialGridDataFrame](#), [gg.SpatialLines](#), [gg.SpatialPixels](#), [gg.SpatialPoints](#), [gg.SpatialPolygons](#), [gg](#), [gm](#)

Examples

```
# Load Gorilla data
data("gorillas")

# Plot Gorilla elevation covariate provided as SpatialPixelsDataFrame.
# The same syntax applies to SpatialGridDataFrame objects.

ggplot() + gg(gorillas$gcov$elevation)

# Add Gorilla survey boundary and nest sightings

ggplot() +
  gg(gorillas$gcov$elevation) +
  gg(gorillas$boundary) +
  gg(gorillas$nests)

# Load pantropical dolphin data

data("mexdolphins")

# Plot the pantropical survey boundary, ship transects and dolphin sightings

ggplot() +
  gg(mexdolphins$ppoly) + # survey boundary as SpatialPolygon
  gg(mexdolphins$samplers) + # ship transects as SpatialLines
  gg(mexdolphins$points) # dolphin sightings as SpatialPoints
```

```

# Change color

ggplot() +
  gg(mexdolphinsppoly, color = "green") + # survey boundary as SpatialPolygon
  gg(mexdolphinsamplers, color = "red") + # ship transects as SpatialLines
  gg(mexdolphinspoints, color = "blue") # dolphin sightings as SpatialPoints

# Visualize data annotations: line width by segment number

names(mexdolphinsamplers) # 'seg' holds the segment number
ggplot() + gg(mexdolphinsamplers, aes(color = seg))

# Visualize data annotations: point size by dolphin group size

names(mexdolphinspoints) # 'size' holds the group size
ggplot() + gg(mexdolphinspoints, aes(size = size))

```

gg.SpatialPoints	<i>Geom for SpatialPoints objects</i>
------------------	---------------------------------------

Description

This function coerces the `SpatialPoints` into a `data.frame` and uses `geom_point` to plot the points.

Usage

```
## S3 method for class 'SpatialPoints'
gg(data, mapping = NULL, crs = NULL, ...)
```

Arguments

<code>data</code>	A <code>SpatialPoints</code> object.
<code>mapping</code>	Aesthetic mappings created by <code>aes</code> or <code>aes_</code> used to update the default mapping. The default mapping is <code>aes_string(x = coordnames(data)[1], y = coordnames(data)[2])</code> .
<code>crs</code>	A <code>CRS</code> object defining the coordinate system to project the data to before plotting.
<code>...</code>	Arguments passed on to <code>geom_point</code> .

Value

A `geom_point` return value

See Also

Other geomes for spatial data: `gg.SpatialGridDataFrame`, `gg.SpatialLines`, `gg.SpatialPixelsDataFrame`, `gg.SpatialPixels`, `gg.SpatialPolygons`, `gg`, `gm`

Examples

```

# Load Gorilla data

data("gorillas")

# Plot Gorilla elevation covariate provided as SpatialPixelsDataFrame.
# The same syntax applies to SpatialGridDataFrame objects.

ggplot() + gg(gorillas$gcov$elevation)

# Add Gorilla survey boundary and nest sightings

ggplot() +
  gg(gorillas$gcov$elevation) +
  gg(gorillas$boundary) +
  gg(gorillas$nest)

# Load pantropical dolphin data

data("mexdolphins")

# Plot the pantropical survey boundary, ship transects and dolphin sightings

ggplot() +
  gg(mexdolphins$poly) + # survey boundary as SpatialPolygon
  gg(mexdolphins$samplers) + # ship transects as SpatialLines
  gg(mexdolphins$points) # dolphin sightings as SpatialPoints

# Change color

ggplot() +
  gg(mexdolphins$poly, color = "green") + # survey boundary as SpatialPolygon
  gg(mexdolphins$samplers, color = "red") + # ship transects as SpatialLines
  gg(mexdolphins$points, color = "blue") # dolphin sightings as SpatialPoints

# Visualize data annotations: line width by segment number

names(mexdolphins$samplers) # 'seg' holds the segment number
ggplot() + gg(mexdolphins$samplers, aes(color = seg))

# Visualize data annotations: point size by dolphin group size

names(mexdolphins$points) # 'size' holds the group size
ggplot() + gg(mexdolphins$points, aes(size = size))

```


Description

Uses the `fortify()` function to turn the `SpatialPolygons` objects into a `data.frame`. Then calls `geom_polygon` to plot the polygons.

Usage

```
## S3 method for class 'SpatialPolygons'  
gg(data, mapping = NULL, crs = NULL,  
    color = "black", alpha = NULL, ...)
```

Arguments

<code>data</code>	A <code>SpatialPolygons</code> object.
<code>mapping</code>	Aesthetic mappings created by <code>aes</code> or <code>aes_</code> used to update the default mapping. The default mapping is <code>aes_string(x = "long", y = "lat", group = "group")</code> .
<code>crs</code>	A <code>CRS</code> object defining the coordinate system to project the data to before plotting.
<code>color</code>	Filling color for the polygons.
<code>alpha</code>	Alpha level for polygon filling.
<code>...</code>	Arguments passed on to <code>geom_polygon</code> .

Value

A `geom_polygon` return value.

See Also

Other geomes for spatial data: `gg.SpatialGridDataFrame`, `gg.SpatialLines`, `gg.SpatialPixelsDataFrame`, `gg.SpatialPixels`, `gg.SpatialPoints`, `gg.gm`

Examples

```
# Load Gorilla data  
data("gorillas")  
  
# Plot Gorilla elevation covariate provided as SpatialPixelsDataFrame.  
# The same syntax applies to SpatialGridDataFrame objects.  
ggplot() + gg(gorillas$gcov$elevation)  
  
# Add Gorilla survey boundary and nest sightings  
ggplot() +  
  gg(gorillas$gcov$elevation) +  
  gg(gorillas$boundary) +  
  gg(gorillas$nests)
```

```

# Load pantropical dolphin data

data("mexdolphins")

# Plot the pantropical survey boundary, ship transects and dolphin sightings

ggplot() +
  gg(mexdolphins$ppoly) + # survey boundary as SpatialPolygon
  gg(mexdolphins$samplers) + # ship transects as SpatialLines
  gg(mexdolphins$points) # dolphin sightings as SpatialPoints

# Change color

ggplot() +
  gg(mexdolphins$ppoly, color = "green") + # survey boundary as SpatialPolygon
  gg(mexdolphins$samplers, color = "red") + # ship transects as SpatialLines
  gg(mexdolphins$points, color = "blue") # dolphin sightings as SpatialPoints

# Visualize data annotations: line width by segment number

names(mexdolphins$samplers) # 'seg' holds the segment number
ggplot() + gg(mexdolphins$samplers, aes(color = seg))

# Visualize data annotations: point size by dolphin group size

names(mexdolphins$points) # 'size' holds the group size
ggplot() + gg(mexdolphins$points, aes(size = size))

```

globe

Plot a globe using rgl

Description

Creates a textured sphere and lon/lat coordinate annotations.

Usage

```
globe(R = 1, R.grid = 1.05, specular = "black", axes = FALSE,
      box = FALSE, xlab = "", ylab = "", zlab = "")
```

Arguments

R	Radius of the globe
R.grid	Radius of the annotation sphere.
specular	Light color of specular effect.
axes	If TRUE, plot x, y and z axes.

box If TRUE, plot a box around the globe.
xlab, ylab, zlab
 Axes labels

Value

No value, used for plotting side effect.

See Also

Other inlabru RGL tools: [glplot.SpatialLines](#), [glplot.SpatialPoints](#), [glplot.inla.mesh](#), [glplot](#)

Examples

```
# Load rgl library (needed due to a bug in sphereplot library)

library(rgl)

# Load pantropoical dolphin data

data("mexdolphin")

# Show the globe

globe()

# Add mesh, ship transects and dolphin sightings stored
# as inla.mesh, SpatialLines and SpatialPoints objects, respectively

glplot(mexdolphin$mesh)
glplot(mexdolphin$samplers)
glplot(mexdolphin$points)
```

glplot

Render Spatial and inla.mesh objects using RGL*

Description

glplot is a generic function for renders various kinds of spatial objects, i.e. Spatial* data and inla.mesh objects. The function invokes particular methods which depend on the class of the first argument.

Usage

```
glplot(object, ...)
```

Arguments

object an object used to select a method.
... further arguments passed to or from other methods.

See Also

Other inlabru RGL tools: [globe](#), [glplot.SpatialLines](#), [glplot.SpatialPoints](#), [glplot.inla.mesh](#)

Examples

```
# Load rgl library (needed due to a bug in sphereplot library)
library(rgl)

# Load pantropoical dolphin data
data("mexdolphins")

# Show the globe
globe()

# Add mesh, ship transects and dolphin sightings stored
# as inla.mesh, SpatialLines and SpatialPoints objects, respectively
glplot(mexdolphins$mesh)
glplot(mexdolphins$samplers)
glplot(mexdolphins$points)
```

glplot.inla.mesh *Visualize SpatialPoints using RGL*

Description

This function transforms the mesh to 3D cartesian coordinates and uses `inla.plot.mesh()` with `rgl=TRUE` to plot the result.

Usage

```
## S3 method for class 'inla.mesh'
glplot(object, add = TRUE, col = NULL, ...)
```

Arguments

object	an inla.mesh object.
add	If TRUE, add the lines to an existing plot. If FALSE, create new plot.
col	Color specification. A single named color, a vector of scalar values, or a matrix of RGB values.
...	Parameters passed on to plot.inla.mesh()

See Also

Other inlabru RGL tools: [globe](#), [glplot.SpatialLines](#), [glplot.SpatialPoints](#), [glplot](#)

Examples

```
# Load rgl library (needed due to a bug in sphereplot library)
library(rgl)

# Load pantropoical dolphin data
data("mexdolphin")

# Show the globe
globe()

# Add mesh, ship transects and dolphin sightings stored
# as inla.mesh, SpatialLines and SpatialPoints objects, respectively

glplot(mexdolphin$mesh)
glplot(mexdolphin$samplers)
glplot(mexdolphin$points)
```

glplot.SpatialLines *Visualize SpatialLines using RGL*

Description

This function will calculate a cartesian representation of the lines provided and use `rgl.linestrip()` in order to render them.

Usage

```
## S3 method for class 'SpatialLines'
glplot(object, add = TRUE, ...)
```

Arguments

object a SpatialLines or SpatialLinesDataFrame object.
add If TRUE, add the lines to an existing plot. If FALSE, create new plot.
... Parameters passed on to rgl.linestrips().

See Also

Other inlabru RGL tools: [globe](#), [glplot.SpatialPoints](#), [glplot.inla.mesh](#), [glplot](#)

Examples

```
# Load rgl library (needed due to a bug in sphereplot library)
library(rgl)

# Load pantropoical dolphin data
data("mexdolphins")

# Show the globe
globe()

# Add mesh, ship transects and dolphin sightings stored
# as inla.mesh, SpatialLines and SpatialPoints objects, respectively
glplot(mexdolphins$mesh)
glplot(mexdolphins$samplers)
glplot(mexdolphins$points)
```

glplot.SpatialPoints *Visualize SpatialPoints using RGL*

Description

This function will calculate the cartesian coordinates of the points provided and use rgl.points() in order to render them.

Usage

```
## S3 method for class 'SpatialPoints'
glplot(object, add = TRUE, color = "red", ...)
```

Arguments

object	a SpatialPoints or SpatialPointsDataFrame object.
add	If TRUE, add the points to an existing plot. If FALSE, create new plot.
color	vector of R color characters. See rgl.material() for details.
...	Parameters passed on to rgl.points()

See Also

Other inlabru RGL tools: [globe](#), [glplot.SpatialLines](#), [glplot.inla.mesh](#), [glplot](#)

Examples

```
# Load rgl library (needed due to a bug in sphereplot library)
library(rgl)

# Load pantropoical dolphin data
data("mexdolphins")

# Show the globe
globe()

# Add mesh, ship transects and dolphin sightings stored
# as inla.mesh, SpatialLines and SpatialPoints objects, respectively

glplot(mexdolphins$mesh)
glplot(mexdolphins$samplers)
glplot(mexdolphins$points)
```

gm

ggplot geom for spatial data

Description

gm is a wrapper for the [gg](#) method. It will take the first argument and transform its coordinate system to latitude and longitude. Thereafter, [gg](#) is called using the transformed data and the arguments provided via `...`. gm is intended to replace gg whenever the data is supposed to be plotted over a spatial map generated by [gmap](#), which only works if the coordinate system is latitude/longitude.

Usage

```
gm(data, ...)
```

Arguments

data an object for which to generate a geom.
 ... Arguments passed on to `gg`.

Value

The form of the value returned by `gm` depends on the class of its argument. See the documentation of the particular methods for details of what is produced by that method.

See Also

Other geomes for inla and inlabru predictions: [gg.data.frame](#), [gg.matrix](#), [gg.prediction](#), [gg](#)
 Other geomes for spatial data: [gg.SpatialGridDataFrame](#), [gg.SpatialLines](#), [gg.SpatialPixelsDataFrame](#),
[gg.SpatialPixels](#), [gg.SpatialPoints](#), [gg.SpatialPolygons](#), [gg](#)
 Other geomes for meshes: [gg.inla.mesh.1d](#), [gg.inla.mesh](#), [gg](#)
 Other geomes for Raster data: [gg.RasterLayer](#), [gg](#)

Examples

```
## Not run:
# Load the Gorilla data
data(gorillas)

# Create a base map centered around the nests and plot the boundary as well as the nests
gmap(gorillas$nests, matype = "satellite") +
  gm(gorillas$boundary) +
  gm(gorillas$nests, color = "white", size = 0.5)

## End(Not run)
```

gmap

Plot a map using extend of a spatial object

Description

Uses `get_map()` to query map services like Google Maps for a region centered around the spatial object provided. Then calls `ggmap()` to plot the map.

Usage

```
gmap(data, ...)
```

Arguments

data A `Spatial*` object.
 ... Arguments passed on to `get_map()`.

Value

a ggplot object

Examples

```
## Not run:
# Load the Gorilla data
data(gorillas)

# Create a base map centered around the nests and plot the boundary as well as the nests
gmap(gorillas$nests, matype = "satellite") +
  gm(gorillas$boundary) +
  gm(gorillas$nests, color = "white", size = 0.5)

## End(Not run)
```

gorillas

Gorilla Nesting Sites.

Description

This the gorillas dataset from the package spatstat, reformatted as point process data for use with inlabru.

Usage

```
data(gorillas)
```

Format

The data are a list that contains these elements:

nests: A SpatialPointsDataFrame object containing the locations of the gorilla nests.

boundary: An SpatialPolygonsDataFrame object defining the boundary of the region that was searched for the nests.

mesh: An inla.mesh object containing a mesh that can be used with function lgcp to fit a LGCP to the nest data.

gcov: A list of SpatialGridDataFrame objects, one for each of these spatial covariates:

aspect Compass direction of the terrain slope. Categorical, with levels N, NE, E, SE, S, SW, W and NW, which are coded as integers 1 to 8.

elevation Digital elevation of terrain, in metres.

heat Heat Load Index at each point on the surface (Beer's aspect), discretised. Categorical with values Warmest (Beer's aspect between 0 and 0.999), Moderate (Beer's aspect between 1 and 1.999), Coolest (Beer's aspect equals 2). These are coded as integers 1, 2 and 3, in that order.

slopangle Terrain slope, in degrees.

sloptype Type of slope. Categorical, with values Valley, Toe (toe slope), Flat, Midslope, Upper and Ridge. These are coded as integers 1 to 6.

vegetation Vegetation type: a categorical variable with 6 levels coded as integers 1 to 6 (in order of increasing expected habitat suitability)

waterdist Euclidean distance from nearest water body, in metres.

plotsample Plot sample of gorilla nests, sampling 9x9 over the region, with 60% coverage. Components:

counts A SpatialPointsDataFrame frame with elements x, y, count, exposure, being the x- and y-coordinates of the centre of each plot, the count in each plot and the area of each plot.

plots A SpatialPolygonsDataFrame defining the individual plot boundaries.

nests A SpatialPointsDataFrame giving the locations of each detected nest.

Source

Library spatstat.

References

Funwi-Gabga, N. (2008) A pastoralist survey and fire impact assessment in the Kagwene Gorilla Sanctuary, Cameroon. M.Sc. thesis, Geology and Environmental Science, University of Buea, Cameroon.

Funwi-Gabga, N. and Mateu, J. (2012) Understanding the nesting spatial behaviour of gorillas in the Kagwene Sanctuary, Cameroon. Stochastic Environmental Research and Risk Assessment 26 (6), 793-811.

Examples

```
data(gorillas) # get the data
# extract all the objects, for convenience:

# plot all the nests, mesh and boundary
ggplot() + gg(gorillas$mesh) + gg(gorillas$boundary) + gg(gorillas$nests)

# Plot the elevation covariate
plot(gorillas$gcov$elevation)

# Plot the plot sample
ggplot() + gg(gorillas$plotsample$plots) + gg(gorillas$plotsample$nests)
```

`init.tutorial`*Global setting for tutorial sessions*

Description

Increases verbosity and sets the inference strategy to empirical Bayes.

Usage

```
init.tutorial()
```

Author(s)

Fabian E. Bachl <<bachlfab@gmail.com>>

Examples

```
## Not run:

# Determine current bru default:
bo = bru.options()

# By default, INLA's integration strategy is set to the INLA default 'auto':
bo$inla.options$control.inla

# Now, let's run init.tutorial() to make empirical Bayes the default
integration method when \code{bru} calls \code{inla}

init.tutorial()

# Check if it worked:
bru.options()$inla.options$control.inla

## End(Not run)
```

`inlabru`*inlabru*

Description

Convenient model fitting using (iterated) INLA.

Details

inlabru facilitates Bayesian spatial modeling using integrated nested Laplace approximations. It is heavily based on R-inla (<http://www.r-inla.org>) but adds additional modeling abilities. Tutorials and more information can be found at <http://www.inlabru.org/>.

The main function for inference using inlabru is `bru`. For point process inference `lgcp` is a good starting point. The package comes with multiple real world data sets, namely `gorillas`, `mexdolphins`, `seals`. Plotting these data sets is straight forward using inlabru's extensions to `ggplot2`, e.g. the `gg` function. For educational purposes some simulated data sets are available as well, e.g. `Poisson1_1D`, `Poisson2_1D`, `Poisson2_2D` and `toygroups`.

Author(s)

Fabian E. Bachl <<bachlfab@gmail.com>>

int

Weighted summation (integration) of data frame subsets

Description

A typical task in statistical inference is to integrate a (multivariate) function along one or more dimensions of its domain. For this purpose, the function is evaluated at some points in the domain and the values are summed up using weights that depend on the area being integrated over. This function performs the weighting and summation conditional for each level of the dimensions that are not integrated over. The parameter `dims` states the dimensions to integrate over. The set of dimensions that are held fixed is the set difference of all column names in `data` and the dimensions stated by `dims`.

Usage

```
int(data, values, dims = NULL)
```

Arguments

<code>data</code>	A data.frame or Spatial object. Has to have a weight column with numeric values.
<code>values</code>	Numerical values to be summed up, usually the result of function evaluations.
<code>dims</code>	Column names (dimension names) of the data object to integrate over.

Value

A data.frame of integrals, one for each level of the cross product of all dimensions not being integrated over.

Examples

```
# Create integration points in two dimensions, x and y

ips = cprod(ipoints(c(0,10), 10, name = "x"),
            ipoints(c(1,5), 10, name = "y"))

# The sizes of the domains are 10 and 4 for x and y, respectively.
# Integrating f(x,y) = 1 along x and y should result in the total
# domain size 40

int(ips, rep(1, nrow(ips)), c("x","y"))
```

<code>ipoints</code>	<i>Generate integration points</i>
----------------------	------------------------------------

Description

This function generates points in one or two dimensions with a weight attached to each point. The weighted sum of a function evaluated at these points is the integral of that function approximated by linear basis functions. The parameter `region` describes the area(s) integrated over.

In case of a single dimension `region` is supposed to be a two-column matrix where each row describes the start and end point of the interval to integrate over. In the two-dimensional case `region` can be either a `SpatialPolygon`, an `inla.mesh` or a `SpatialLinesDataFrame` describing the area to integrate over. If a `SpatialLineDataFrame` is provided it has to have a column called 'weight' in order to indicate the width of the line.

The `domain` parameter is an `inla.mesh.1d` or `inla.mesh` object that can be employed to project the integration points to the vertices of the mesh. This reduces the final number of integration points and reduces the computational cost of the integration. The projection can also prevent numerical issues in spatial LGCP models where each observed point is ideally surrounded by three integration point sitting at the corresponding mesh vertices. For convenience, the `domain` parameter can also be a single integer setting the number of equally spaced integration points in the one-dimensional case.

Usage

```
ipoints(region = NULL, domain = NULL, name = "x", group = NULL, project)
```

Arguments

<code>region</code>	Description of the integration region boundary. In 1D either a vector of two numerics or a two-column matrix where each row describes an interval. In 2D either a <code>SpatialPolygon</code> or a <code>SpatialLinesDataFrame</code> with a weight column defining the width of the line.
---------------------	--

domain	In 1D a single numeric setting the number of integration points or an <code>inla.mesh.1d</code> defining the locations to project the integration points to. In 2D domain has to be an <code>inla.mesh</code> object describing the projection and granularity of the integration.
name	Character array stating the name of the domains dimension(s)
group	Column names of the region object (if applicable) for which the integration points are calculated independently and not merged by the projection.
project	If TRUE, project the integration points to mesh vertices

Value

A data.frame or SpatialPointsDataFrame of 1D and 2D integration points, respectively.

Author(s)

Fabian E. Bachl <<bachlfab@gmail.com>>

Examples

```
# Create 50 integration points covering the dimension 'myDim' between 0 and 10.

ips = ipoints(c(0,10), 50, name = "myDim")
plot(ips)

# Create integration points for the two intervals [0,3] and [5,10]

ips = ipoints(matrix(c(0,3, 5,10), nrow = 2, byrow = TRUE), 50)
plot(ips)

# Convert a 1D mesh into integration points
library(INLA)
mesh = inla.mesh.1d(seq(0,10,by = 1))
ips = ipoints(mesh, name = "time")
plot(ips)

# Obtain 2D integration points from a SpatialPolygon

data(gorillas, package = "inlabru")
ips = ipoints(gorillas$boundary)
ggplot() + gg(gorillas$boundary) + gg(ips, aes(size = weight))

#' Project integration points to mesh vertices

ips = ipoints(gorillas$boundary, domain = gorillas$mesh)
ggplot() + gg(gorillas$mesh) + gg(gorillas$boundary) + gg(ips, aes(size = weight))
```

```
# Turn a 2D mesh into integration points

ips = ipoints(gorillas$mesh)
ggplot() + gg(gorillas$boundary) + gg(ips, aes(size = weight))
```

lgcp

Log Gaussian Cox process (LGCP) inference using INLA

Description

This function performs inference on a LGCP observed via points residing possibly multiple dimensions. These dimensions are defined via the left hand side of the formula provided via the model parameter. The left hand side determines the intensity function that is assumed to drive the LGCP. This may include effects that lead to a thinning (filtering) of the point process. By default, the log intensity is assumed to be a linear combination of the effects defined by the formula's RHS. More sophisticated models, e.g. non-linear thinning, can be achieved by using the predictor argument. The latter requires multiple runs of INLA for improving the required approximation of the predictor. In many applications the LGCP is only observed through subsets of the dimensions the process is living in. For example, spatial point realizations may only be known in sub-areas of the modeled space. These observed subsets of the LGCP domain are called samplers and can be provided via the respective parameter. If samplers is NULL it is assumed that all of the LGCP's dimensions have been observed completely.

Usage

```
lgcp(components, data, samplers = NULL, domain = NULL, ips = NULL,
      formula = . ~ ., E = 1, options = list())
```

Arguments

components	A formula describing the latent components
data	A data frame or SpatialPoints[DataFrame] object
samplers	A data frame or Spatial[Points/Lines/Polygons]DataFrame objects
domain	Named list of domain definitions
ips	Integration points (overrides samplers)
formula	If NULL, the linear combination implied by the components is used as a predictor for the point location intensity. If a (possibly non-linear) expression is provided the respective Taylor approximation is used as a predictor. Multiple runs if INLA are then required for a better approximation of the posterior.
E	Single numeric used rescale all integration weights by a fixed factor
options	See bru.options

Value

An `bru` object

Examples

```
## Not run:

Load the Gorilla data
data(gorillas)

# Use tutorial setting and thus empirical Bayes for faster inference
init.tutorial()

# Plot the Gorilla nests, the mesh and the survey boundary
ggplot() +
  gg(gorillas$mesh) +
  gg(gorillas$nests) +
  gg(gorillas$boundary) +
  coord_fixed()

# Define SPDE prior
matern <- inla.spde2.pcmatern(gorillas$mesh,
                             prior.sigma = c(0.1, 0.01),
                             prior.range = c(5, 0.01))

# Define domain of the LGCP as well as the model components (spatial SPDE effect and Intercept)
cmp <- coordinates ~ mySmooth(map = coordinates, model = matern) + Intercept

# Fit the model
fit <- lgcp(cmp, gorillas$nests, samplers = gorillas$boundary)

# Predict the spatial intensity surface
lambda <- predict(fit, pixels(gorillas$mesh), ~ exp(mySmooth + Intercept))

# Plot the intensity
ggplot() +
  gg(lambda) +
  gg(gorillas$mesh) +
  gg(gorillas$nests) +
  gg(gorillas$boundary) +
  coord_fixed()

## End(Not run)
```


Description

Likelihood construction for usage with [bru](#)

Usage

```
like(family, formula = . ~ ., data = NULL, components = NULL,  
     mesh = NULL, E = 1, samplers = NULL, ips = NULL, domain = NULL)
```

Arguments

family	A character identifying a valid inla likelihood. Alternatively 'cp' for Cox processes.
formula	a formula where the right hand side expression defines the predictor used in the optimization.
data	Likelihood-specific data.
components	Components.
mesh	An inla.mesh object.
E	Exposure parameter for family = 'poisson' passed on to inla . Special case if family is 'cp': rescale all integration weights by E.
samplers	Integration domain for 'cp' family.
ips	Integration points for 'cp' family. Overrides samplers.
domain	Named list of domain definitions.

Value

A likelihood configuration which can be used to parameterize [bru](#).

Author(s)

Fabian E. Bachl <<bachlfab@gmail.com>>

Examples

```
# The like function's main purpose is to set up models with multiple likelihoods.  
# The following example generates some random covariates which are observed through  
# two different random effect models with different likelihoods  
  
# Generate the data  
  
set.seed(123)  
  
n1 = 200  
n2 = 10  
  
x1 = runif(n1)  
x2 = runif(n2)  
z2 = runif(n2)
```

```

y1 = rnorm(n1, mean = 2 * x1 + 3)
y2 = rpois(n2, lambda = exp(2 * x2 + z2 + 3))

df1 = data.frame(y = y1, x = x1)
df2 = data.frame(y = y2, x = x2, z = z2)

# Single likelihood models and inference using bru are done via

cmp1 = y ~ x + Intercept
fit1 = bru(cmp1, family = "gaussian", data = df1)
summary(fit1)

cmp2 = y ~ x + z + Intercept
fit2 = bru(cmp2, family = "poisson", data = df2)
summary(fit2)

# A joint model has two likelihoods, which are set up using the like function

lik1 = like("gaussian", formula = y ~ x + Intercept, data = df1)
lik2 = like("poisson", formula = y ~ x + z + Intercept, data = df2)

# The union of effects of both models gives the components needed to run bru

jcmp = y ~ x + z + Intercept
jfit = bru(jcmp, lik1, lik2)

# Compare the estimates

p1 = ggplot() + gg(fit1$summary.fixed, bar = TRUE) + ylim(0, 4) + ggtitle("Model 1")
p2 = ggplot() + gg(fit2$summary.fixed, bar = TRUE) + ylim(0, 4) + ggtitle("Model 2")
pj = ggplot() + gg(jfit$summary.fixed, bar = TRUE) + ylim(0, 4) + ggtitle("Joint model")

multiplot(p1, p2, pj)

```

mexdolphins

Pan-tropical spotted dolphins in the Gulf of Mexico.

Description

This is a version of the mexdolphins dataset from the package `dsm`, reformatted as point process data for use with `inlabru`. The data are from a combination of several NOAA shipboard surveys conducted on pan-tropical spotted dolphins in the Gulf of Mexico. 47 observations of groups of dolphins were detected. The group size was recorded, as well as the Beaufort sea state at the time of the observation.

Usage

```
mexdolphins
```

Format

A list of objects:

points: A `SpatialPointsDataFrame` object containing the locations of detected dolphin groups, with their size as an attribute.

samplers: A `SpatialLinesDataFrame` object containing the transect lines that were surveyed.

mesh: An `inla.mesh` object containing a Delaunay triangulation mesh (a type of discretization of continuous space) covering the survey region.

ppoly: An `SpatialPolygonsDataFrame` object defining the boundary of the survey region.

simulated: A `SpatialPointsDataFrame` object containing the locations of a *simulated* population of dolphin groups. The population was simulated from a 'codeinlabru model fitted to the actual survey data. Note that the simulated data do not have any associated size information.

Source

Library dsm.

References

Halpin, P.N., A.J. Read, E. Fujioka, B.D. Best, B. Donnelly, L.J. Hazen, C. Kot, K. Urian, E. LaBrecque, A. Dimatteo, J. Cleary, C. Good, L.B. Crowder, and K.D. Hyrenbach. 2009. OBIS-SEAMAP: The world data center for marine mammal, sea bird, and sea turtle distributions. *Oceanography* 22(2):104-115

NOAA Southeast Fisheries Science Center. 1996. Report of a Cetacean Survey of Oceanic and Selected Continental Shelf Waters of the Northern Gulf of Mexico aboard NOAA Ship Oregon II (Cruise 220)

Examples

```
data(mexdolphins, package="inlabru")
plot(mexdolphins$mesh, edge.color="lightgray", draw.segments=FALSE) # draw mesh
plot(mexdolphins$ppoly, add=TRUE) # add survey region boundary
plot(mexdolphins$samplers, col="blue", add=TRUE) # draw transects (in and out of survey region)
grsize = attributes(mexdolphins$points)$data[, "size"] # Get group size data
plot(mexdolphins$points, pch=19, col="red", cex=log(grsize/30), add=TRUE)
```

Description

Data imported from package MRSea, see <http://creem2.st-andrews.ac.uk/software/>

Usage

```
mrsea
```

Format

A list of objects:

points: A `SpatialPointsDataFrame` object containing the locations of XXXXX.

samplers: A `SpatialLinesDataFrame` object containing the transect lines that were surveyed.

mesh: An `inla.mesh` object containing a Delaunay triangulation mesh (a type of discretization of continuous space) covering the survey region.

boundary: An `SpatialPolygonsDataFrame` object defining the boundary of the survey region.

covar: An `SpatialPointsDataFrame` containing sea depth estimates.

Source

Library MRSea.

References

NONE YET

Examples

```
data(mrsea)
ggplot() + gg(mrsea$mesh) + gg(mrsea$samplers) + gg(mrsea$points) + gg(mrsea$boundary)
```

multiplot

Multiple ggplots on a page.

Description

Renders multiple ggplots on a single page.

Usage

```
multiplot(..., plotlist = NULL, cols = 1, layout = NULL)
```

Arguments

<code>...</code>	Comma-separated ggplot objects.
<code>plotlist</code>	A list of ggplot objects - an alternative to the comma-separated argument above.
<code>cols</code>	Number of columns of plots on the page.
<code>layout</code>	A matrix specifying the layout. If present, 'cols' is ignored. If the layout is something like <code>matrix(c(1,2,3,3), nrow=2, byrow=TRUE)</code> , then plot 1 will go in the upper left, 2 will go in the upper right, and 3 will go all the way across the bottom.

Author(s)

David L. Borchers <<dlb@st-andrews.ac.uk>>

Source

[http://www.cookbook-r.com/Graphs/Multiple_graphs_on_one_page_\(ggplot2\)/](http://www.cookbook-r.com/Graphs/Multiple_graphs_on_one_page_(ggplot2)/)

Examples

```
df = data.frame(x=1:10,y=1:10,z=11:20)
p11 = ggplot(data = df) + geom_line(mapping = aes(x,y), color = "red")
p12 = ggplot(data = df) + geom_line(mapping = aes(x,z), color = "blue")
multiplot(p11,p12, cols = 2)
```

pixels

Generate SpatialPixels covering an inla.mesh

Description

Generate SpatialPixels covering an inla.mesh

Usage

```
pixels(mesh, nx = 150, ny = 150, mask = TRUE)
```

Arguments

mesh	An inla.mesh object
nx	Number of pixels in x direction
ny	Number of pixels in y direction
mask	If logical and TRUE, remove pixels that are outside the mesh. If mask is a Spatial object, only return pixels covered by this object.

Value

SpatialPixels covering the mesh

Author(s)

Fabian E. Bachl <<bachlfab@gmail.com>>

Examples

```
data("mrsea")
px1 = pixels(mrsea$mesh, nx = 50, ny = 50)
ggplot() + gg(px1) + gg(mrsea$mesh)
```

`plot.bru`*Plot method for posterior marginals estimated by [bru](#)*

Description

[bru](#) uses [inla](#) to fit models. The latter estimates the posterior densities of all random effects in the model. This function serves to access and plot the posterior densities in a convenient way.

Usage

```
## S3 method for class 'bru'  
plot(x, ...)
```

Arguments

`x` a fitted [bru](#) model.
`...` A character naming the effect to plot, e.g. "Intercept".

Value

an object of class `gg`

Examples

```
## Not run:  
  
# Generate some data and fit a simple model  
input.df <- data.frame(x=cos(1:10))  
input.df <- within(input.df, y <- 5 + 2*cos(1:10) + rnorm(10, mean=0, sd=0.1))  
fit <- bru(y ~ x, "gaussian", input.df)  
summary(fit)  
  
# Plot the posterior of the model's x-effect  
plot(fit, "x")  
  
## End(Not run)
```

plot.prediction	<i>Plot prediction using ggplot2</i>
-----------------	--------------------------------------

Description

Generates a base ggplot2 using [ggplot](#) and adds a geom for input x using [gg](#).

Usage

```
## S3 method for class 'prediction'  
plot(x, y = NULL, ...)
```

Arguments

x	a prediction object.
y	Ignored argument but required for S3 compatibility.
...	Arguments passed on to gg.prediction .

Value

an object of class gg

Examples

```
# Generate some data  
  
input.df <- data.frame(x=cos(1:10))  
input.df <- within(input.df, y <- 5 + 2*cos(1:10) + rnorm(10, mean=0, sd=0.1))  
  
# Fit a model with fixed effect 'x' and intercept 'Intercept'  
  
fit <- bru(y ~ x, "gaussian", input.df)  
  
# Predict posterior statistics of 'x'  
  
xpost = predict(fit, formula = ~ x)  
  
# The statistics include mean, standard deviation, the 2.5% quantile, the median,  
# the 97.5% quantile, minimum and maximum sample drawn from the posterior as well as  
# the coefficient of variation and the variance.  
  
xpost  
  
# For a single variable like 'x' the default plotting method invoked by gg() will  
# show these statistics in a fashion similar to a box plot:  
ggplot() + gg(xpost)
```

```

# The predict function can also be used to simulatenneously estimate posteriors
# of multiple variables:

xipost = predict(fit, formula = ~ data.frame(post = c(Intercept, x)))
xipost

# If we still want a plot in the previous style we have to set the bar parameter to TRUE

rownames(xipost) = c("Intercept", "x")
p1 = ggplot() + gg(xipost, bar = TRUE)
p1

# Note that gg also understands the posterior estimates generated while running INLA

p2 = ggplot() + gg(fit$summary.fixed, bar = TRUE)
multiplot(p1, p2)

# By default, if the prediction has more than one row, gg will plot the column 'mean' against
# the row index. This is for instance usefuul for predicting and plotting function
# but not very meaningful given the above example:

ggplot() + gg(xipost)

# For ease of use we can also type

plot(xipost)

# This type of plot will show a ribbon around the mean, which viszualizes the upper and lower
# quantiles mentioned above (2.5 and 97.5%). Plotting the ribbon can be turned of using the
# \code{ribbon} parameter

ggplot() + gg(xipost, ribbon = FALSE)

# Much like the other geomes produced by gg we can adjust the plot using ggplot2 style
# commands, for instance

ggplot() +
  gg(xipost) +
  gg(xipost, mapping = aes(y = median), ribbon = FALSE, color = "red")

```

plotsample

Create a plot sample.

Description

Creates a plot sample on a regular grid with a random start location.

Usage

```
plotsample(spdf, boundary, x.ppn = 0.25, y.ppn = 0.25, nx = 5, ny = 5)
```

Arguments

spdf	A SpatialPointsDataFrame defining the points that are to be sampled by the plot sample.
boundary	A SpatialPolygonsDataFrame defining the survey boundary within which the points occur.
x.ppn	The proportion of the x=axis that is to be included in the plots.
y.ppn	The proportion of the y=axis that is to be included in the plots.
nx	The number of plots in the x-dimension.
ny	The number of plots in the y-dimension.

Value

A list with three components:

plots: A SpatialPolygonsDataFrame object containing the plots that were sampled.

dets: A SpatialPointsDataFrame object containing the locations of the points within the plots.

counts: A dataframe containing the following columns

x: The x-coordinates of the centres of the plots within the boundary.

y: The y-coordinates of the centres of the plots within the boundary.

n: The numbers of points in each plot.

area: The areas of the plots within the boundary

Examples

```
library(raster)
data(gorillas)
plotpts = plotsample(gorillas$nestst,gorillas$boundary,x.ppn=0.4,y.ppn=0.4,nx=5,ny=5)
ggplot() +gg(plotpts$plots) +gg(plotpts$dets,pch="+",cex=2) +gg(gorillas$boundary)
```

point2count	<i>Convert a plot sample of points into one of counts.</i>
-------------	--

Description

Converts a plot sample with locations of each point within each plot, into a plot sample with only the count within each plot.

Usage

```
point2count(plots, dets)
```

Arguments

plots	A SpatialPolygonsDataFrame object containing the plots that were sampled.
dets	A SpatialPointsDataFrame object containing the locations of the points within the plots.

Value

A SpatialPolygonsDataFrame with counts in each plot contained in slot @data\$n.

Examples

```
library(raster)
data(gorillas)
plotpts = plotsample(gorillas$neests,gorillas$boundary,x.ppn=0.4,y.ppn=0.4,nx=5,ny=5)
p1 = ggplot() +gg(plotpts$plots) +gg(plotpts$dets) +gg(gorillas$boundary)
countdata = point2count(plotpts$plots,plotpts$dets)
x=coordinates(countdata)[,1]
y=coordinates(countdata)[,2]
count=countdata@data$n
p2 = ggplot() +gg(gorillas$boundary) +gg(plotpts$plots) + geom_text(aes(label=count, x=x, y=y))
multiplot(p1,p2,cols=2)
```

Poisson1_1D	<i>1-Dimensional Homogeneous Poisson example.</i>
-------------	---

Description

Point data and count data, together with intensity function and expected counts for a homogeneous 1-dimensional Poisson process example.

Usage

```
data(Poisson1_1D)
```

Format

The data contain the following R objects:

lambda1_1D: A function defining the intensity function of a nonhomogeneous Poisson process.
Note that this function is only defined on the interval (0,55).

E_nc1 The expected counts of the gridded data.

pts1 The locations of the observed points (a data frame with one column, named x).

countdata1 A data frame with three columns, containing the count data:

x The grid cell midpoint.

count The number of detections in the cell.

exposure The width of the cell.

Examples

```
library(ggplot2)
data(Poisson1_1D)
ggplot(countdata1) +
  geom_point(data = countdata1, aes(x=x,y=count),col="blue") +ylim(0,max(countdata1$count)) +
  geom_point(data = pts1, aes(x=x), y = 0.2, shape = "|",cex=4) +
  geom_point(data = countdata1, aes(x=x), y = 0, shape = "+",col="blue",cex=4) +
  xlab(expression(bold(s))) +ylab("count")
```

Poisson2_1D

1-Dimensional NonHomogeneous Poisson example.

Description

Point data and count data, together with intensity function and expected counts for a unimodal nonhomogeneous 1-dimensional Poisson process example.

Usage

```
data(Poisson2_1D)
```

Format

The data contain the following R objects:

`lambda2_1D`: A function defining the intensity function of a nonhomogeneous Poisson process.

Note that this function is only defined on the interval (0,55).

`cov2_1D`: A function that gives what we will call a 'habitat suitability' covariate in 1D space.

`E_nc2` The expected counts of the gridded data.

`pts2` The locations of the observed points (a data frame with one column, named `x`).

`countdata2` A data frame with three columns, containing the count data:

`x` The grid cell midpoint.

`count` The number of detections in the cell.

`exposure` The width of the cell.

Examples

```
library(ggplot2)
data(Poisson2_1D)
p1 = ggplot(countdata2) +
  geom_point(data = countdata2, aes(x=x,y=count),col="blue") +ylim(0,max(countdata2$count,E_nc2)) +
  geom_point(data = countdata2, aes(x=x), y = 0, shape = "+",col="blue",cex=4) +
  geom_point(data=data.frame(x=countdata2$x,y=E_nc2), aes(x=x), y = E_nc2, shape = "_",cex=5) +
  xlab(expression(italic(s))) +ylab("count")
ss = seq(0,55,length=200)
lambda = lambda2_1D(ss)
p2 = ggplot() +
  geom_line(data=data.frame(x=ss,y=lambda), aes(x=x,y=y),col="blue") +ylim(0,max(lambda)) +
  geom_point(data = pts2, aes(x=x), y = 0.2, shape = "|",cex=4) +
  xlab(expression(italic(s))) +ylab(expression(lambda(italic(s))))
multiplot(p1,p2,cols=1)
```

Poisson3_1D

1-Dimensional NonHomogeneous Poisson example.

Description

Point data and count data, together with intensity function and expected counts for a multimodal nonhomogeneous 1-dimensional Poisson process example. Counts are given for two different gridded data interval widths.

Usage

```
data(Poisson3_1D)
```

Format

The data contain the following R objects:

`lambda3_1D`: A function defining the intensity function of a nonhomogeneous Poisson process.

Note that this function is only defined on the interval (0,55).

`E_nc3a` The expected counts of gridded data for the wider bins (10 bins).

`E_nc3b` The expected counts of gridded data for the wider bins (20 bins).

`pts3` The locations of the observed points (a data frame with one column, named `x`).

`countdata3a` A data frame with three columns, containing the count data for the 10-interval case:

`countdata3b` A data frame with three columns, containing the count data for the 20-interval case:

`x` The grid cell midpoint.

`count` The number of detections in the cell.

`exposure` The width of the cell.

Examples

```
library(ggplot2)
data(Poisson3_1D)
# first the plots for the 10-bin case:
p1a = ggplot(countdata3a) +
  geom_point(data = countdata3a, aes(x=x,y=count),col="blue") +ylim(0,max(countdata3a$count,E_nc3a)) +
  geom_point(data = countdata3a, aes(x=x), y = 0, shape = "+",col="blue",cex=4) +
  geom_point(data=data.frame(x=countdata3a$x,y=E_nc3a), aes(x=x), y = E_nc3a, shape = "_",cex=5) +
  xlab(expression(italic(s))) +ylab("count")
ss = seq(0,55,length=200)
lambda = lambda3_1D(ss)
p2a = ggplot() +
  geom_line(data=data.frame(x=ss,y=lambda), aes(x=x,y=y),col="blue") +ylim(0,max(lambda)) +
  geom_point(data = pts3, aes(x=x), y = 0.2, shape = "|",cex=4) +
  xlab(expression(italic(s))) +ylab(expression(lambda(italic(s))))
multiplot(p1a,p2a,cols=1)

# Then the plots for the 20-bin case:
p1a = ggplot(countdata3b) +
  geom_point(data = countdata3b, aes(x=x,y=count),col="blue") +
  ylim(0,max(countdata3b$count,E_nc3b)) +
  geom_point(data = countdata3b, aes(x=x), y = 0, shape = "+",col="blue",cex=4) +
  geom_point(data=data.frame(x=countdata3b$x,y=E_nc3b), aes(x=x), y = E_nc3b, shape = "_",cex=5) +
  xlab(expression(italic(s))) +ylab("count")
ss = seq(0,55,length=200)
lambda = lambda3_1D(ss)
p2a = ggplot() +
  geom_line(data=data.frame(x=ss,y=lambda), aes(x=x,y=y),col="blue") +ylim(0,max(lambda)) +
  geom_point(data = pts3, aes(x=x), y = 0.2, shape = "|",cex=4) +
  xlab(expression(italic(s))) +ylab(expression(lambda(italic(s))))
multiplot(p1a,p2a,cols=1)
```

predict.bru	<i>Prediction from fitted bru model</i>
-------------	---

Description

Takes a fitted bru object produced by the function `bru()` and produces predictions given a new set of values for the model covariates or the original values used for the model fit. The predictions can be based on any R expression that is valid given these values/covariates and the joint posterior of the estimated random effects.

Mean value predictions are accompanied by the standard errors, upper and lower 2.5 median, variance, coefficient of variation as well as the variance and minimum and maximum sample value drawn in course of estimating the statistics.

Usage

```
## S3 method for class 'bru'
predict(object, data = NULL, formula = NULL,
        n.samples = 100, ...)
```

Arguments

object	An object obtained by calling <code>bru</code> or <code>lgcp</code> .
data	A data.frame or SpatialPointsDataFrame of covariates needed for the prediction.
formula	A formula determining which effects to predict and how to combine them.
n.samples	Integer setting the number of samples to draw in order to calculate the posterior statistics. The default is rather low but provides a quick approximate result.
...	ignored arguments (S3 generic compatibility).

Details

Internally, this method calls `generate.bru` in order to draw samples from the model.

Value

a data.frame or Spatial* object with predicted mean values and other summary statistics attached.

Examples

```
# Load INLA
library(INLA)

# Load the Gorilla data
data(gorillas)

# Use tutorial setting and thus empirical Bayes for faster inference
```

```
init.tutorial()

# Plot the Gorilla nests, the mesh and the survey boundary

ggplot() +
  gg(gorillas$mesh) +
  gg(gorillas$nests) +
  gg(gorillas$boundary) +
  coord_fixed()

# Define SPDE prior

matern <- inla.spde2.pcmatern(gorillas$mesh,
                             prior.sigma = c(0.1, 0.01),
                             prior.range = c(5, 0.01))

# Define domain of the LGCP as well as the model components (spatial SPDE effect and Intercept)

cmp <- coordinates ~ mySmooth(map = coordinates, model = matern) + Intercept

# Fit the model
fit <- lgcp(cmp, gorillas$nests, samplers = gorillas$boundary)

# Once we obtain a fitted model the predict function can serve various purposes.
# The most basic one is to determine posterior statistics of a univariate
# random variable in the model, e.g. the intercept

icpt <- predict(fit, NULL, ~ Intercept)
rownames(icpt) = "Intercept"
plot(icpt)

# The formula argument can take any expression that is valid within the model, for
# instance a non-linear transformation of a random variable

exp.icpt <- predict(fit, NULL, ~ exp(Intercept))
rownames(exp.icpt) = "exp(Intercept)"
plot(rbind(icpt, exp.icpt), bar = TRUE)

# The intercept is special in the sense that it does not depend on other variables
# or covariates. However, this is not true for the smooth spatial effects 'mySmooth'.
# In order to predict 'mySmooth' we have to define where (in space) to predict. For
# this purpose, the second argument of the predict function can take {data.frame}
# objects as well as Spatial objects. For instance, we might want to predict
# 'mySmooth' at the locations of the mesh vertices. Using

vrt = vertices(gorillas$mesh)

# we obtain these vertices as a SpatialPointsDataFrame

ggplot() + gg(gorillas$mesh) + gg(vrt, color = "red")

# Predicting 'mySmooth' at these locations works as follows
```

```

mySmooth = predict(fit, vrt, ~ mySmooth)

# Note that just like the input also the output will be a SpatialPointsDataFrame
# and that the predicted statistics are simply added as columns

class(mySmooth)
head(vrt)
head(mySmooth)

# Plotting the mean, for instance, at the mesh node is straight forward

ggplot() +
  gg(gorillas$mesh) +
  gg(mySmooth, aes(color = mean), size = 3)

# However, we are often interested in a spatial field and thus a linear interpolation,
# which can be achieved by using the gg mechanism for meshes

ggplot() + gg(gorillas$mesh, color = mySmooth$mean)

# Alternatively, we can predict the spatial field at a grid of locations, e.g. a
# SpatialPixels object covering the mesh

pxl = pixels(gorillas$mesh)
mySmooth = predict(fit, pxl, ~ mySmooth)

# This will give us a SpatialPixelDataFrame with the columns we are looking for

head(mySmooth)
ggplot() + gg(mySmooth)

```

predict.inla

Prediction from fitted inla model

Description

Takes a fitted inla object produced by the function `inla()` and produces predictions given a new set of values for the model covariates or the original values used for the model fit. The predictions can be based on any R expression that is valid given these values/covariates and the posterior of the estimated effects.

Usage

```

## S3 method for class 'inla'
predict(object, ...)

```


Arguments

object An object obtained by calling `bru` or `lgcp`.
... Arguments passed on to `predict.bru()`.

Details

IMPORTANT: The `inla` object provided has to have an additional field called "formula". This is the formula used to call the `inla()` function and will be used to convert the `inla` object to a `bru` object. Thereafter, `preict.bru()` is called to perform the prediction.

Value

A prediction object.

Author(s)

Fabian E. Bachl <<bachlfab@gmail.com>>

Examples

```
## Not run:  
  
# Generate some data  
  
input.df <- data.frame(x=cos(1:10))  
input.df <- within(input.df, y <- 5 + 2*cos(1:10) + rnorm(10, mean=0, sd=0.1))  
  
# Fit a Gaussian likelihood model  
  
formula = y ~ x  
fit <- inla(formula, "gaussian", data = input.df, control.compute=list(config = TRUE))  
  
# Add formula to inla object  
  
fit$formula = y ~ x  
  
Estimate posterior statistics of  $\exp(x)$ , where  $x$  is the random effect.  
  
xpost = predict(fit, NULL, ~ exp(x))  
xpost  
plot(xpost)  
  
## End(Not run)
```

 sample.lgcp

Sample from an inhomogeneous Poisson process

Description

This function provides point samples from one- and two-dimensional inhomogeneous Poisson processes. The log intensity has to be provided via its values at the nodes of an `inla.mesh.1d` or `inla.mesh` object. In between mesh nodes the log intensity is assumed to be linear.

Usage

```
sample.lgcp(mesh, loglambda, strategy = "rectangle", R = 6371,
            samplers = NULL)
```

Arguments

mesh	An inla.mesh object
loglambda	A vector of log intensities at the mesh vertices (for higher order basis functions, e.g. for <code>inla.mesh.1d</code> meshes, <code>loglambda</code> should be given as <code>mesh\$m</code> basis function weights rather than the values at the <code>mesh\$n</code> vertices)
strategy	Only relevant for 2D meshes. Use "rectangle" for flat 2D meshes and "spherical" or "sliced-spherical" for spherical meshes.
R	Numerical value only applicable to spherical meshes. This sets the radius of the sphere approximated by the mesh. The default is 6371, which is approximately the radius of the earth in kilometers.
samplers	A <code>SpatialPolygonsDataFrame</code> . Simulated points that fall outside these polygons are discarded.

Details

For 2D processes on a sphere the `R` parameter can be used to adjust to sphere's radius implied by the mesh. If the intensity is very high the standard strategy "spherical" can cause memory issues. Using the "sliced-spherical" strategy can help in this case.

Value

A `data.frame` (1D case) or `SpatialPoints` (2D case) object of point locations.

Author(s)

Daniel Simpson <<dp.simpson@gmail.com>> (base algorithm), Fabian E. Bachl <<bachlfab@gmail.com>> (inclusion in `inlabru`, sliced spherical sampling)

Examples

```
library(INLA)
vertices = seq(0, 3, by = 0.1)
mesh = inla.mesh.1d(vertices)
loglambda = 5-0.5*vertices
pts = sample.lgcp(mesh, loglambda)
pts$y = 0
plot(vertices, exp(loglambda), type = "l", ylim = c(0,150))
points(pts, pch = "|" )
```

```
data("gorillas")
pts = sample.lgcp(gorillas$mesh, rep(1.5, gorillas$mesh$n))
ggplot() + gg(gorillas$mesh) + gg(pts)
```

seals

Seal pups

Description

This is a single transect of an aerial photo seal pup survey in the Greenland Sea

Usage

```
data(seals)
```

Format

The data contain these objects:

points: A SpatialPointsDataFrame Center locations of the photos

mesh: An inla.mesh enclosing the plane's transect

ice.data: An SpatialPointsDataFrame with MODIS ice concentration estimates

ice.cv: An covdata object with interpolated ice coverage data

Source

Martin Jullum <<Martin.Jullum@nr.no>>

References

Oigard, T. A. (2013) From pup production to quotas: current status of harp seals in the Greenland Sea. ICES Journal of Marine Science, doi.10.1093/icesjms/fst155.

Oigard, T. A. (2014) Current status of hooded seals in the Greenland Sea. Victims of climate change and predation?, Biological Conservation , 2014, 172, 29 - 36.

Examples

```
data(seals)
ggplot() + gg(seals$mesh) + gg(seals$points)
```

sline

Convert data frame to SpatialLinesDataFrame

Description

A line in 2D space is defined by a start and an end point, each associated with 2D coordinates. This function takes a `/codedata.frame` as input and assumes that each row defines a line in space. In order to do so, the data frame must have at least four columns and the `start.cols` and `end.cols` parameters must be used to point out the names of the columns that define the start and end coordinates of the line. The data is then converted to a `SpatialLinesDataFrame` DF. If a coordinate reference system `crs` is provided it is attached to DF. If also `to.crs` is provided, the coordinate system of DF is transformed accordingly. Additional columns of the input data, e.g. covariates, are retained and attached to DF.

Usage

```
sline(data, start.cols, end.cols, crs = CRS(as.character(NA)),
      to.crs = NULL)
```

Arguments

<code>data</code>	A <code>data.frame</code>
<code>start.cols</code>	Character array pointing out the columns of data that hold the start points of the lines
<code>end.cols</code>	Character array pointing out the columns of data that hold the end points of the lines
<code>crs</code>	Coordinate reference system of the original data
<code>to.crs</code>	Coordinate reference system for the <code>SpatialLines</code> output.

Value

`SpatialLinesDataFrame`

Examples

```
# Create a data frame defining three lines
lns = data.frame(xs = c(1,2,3), ys = c(1,1,1), # start points
                xe = c(2,3,4), ye = c(2,2,2)) # end points
```

```
# Conversion to SpatialLinesDataFrame without CRS
spl = sline(lns, start.cols = c("xs", "ys"),
           end.cols = c("xe", "ye"))

# Plot the lines
ggplot() + gg(spl)
```

spatial.to.ppp

Convert SpatialPoints and boundary polygon to spatstat ppp object

Description

Spatstat point pattern objects consist of points and an observation windows. This function uses a SpatialPoints object and a SpatialPolygon object to generate the points and the window. Lastly, the ppp() function is called to create the ppp object.

Usage

```
spatial.to.ppp(points, samplers)
```

Arguments

points	A SpatialPoints[DataFrame] object describing the point pattern.
samplers	A SpatialPolygons[DataFrame] object describing the observation window.
...	arguments passed on to predict

Value

A spatstat spatstat ppp object

Examples

```
# Load Gorilla data

data("gorillas", package = "inlabru")

# Use nest locations and survey boundary to create a spatstat ppp object

gp <- spatial.to.ppp(gorillas$nest, gorillas$boundary)
class(gp)

# Plot it

plot(gp)
```

spde.posterior	<i>Posteriors of SPDE hyper parameters and Matern correlation or covariance function.</i>
----------------	---

Description

Calculate posterior distribution of the range, log(range), variance, or log(variance) parameter of a model's SPDE component. Can also plot Matern correlation or covariance function. `inla.spde.result`.

Usage

```
spde.posterior(result, name, what = "range")
```

Arguments

result	An object inheriting from <code>inla</code> .
name	Character stating the name of the SPDE effect, see <code>names(result\$summary.random)</code> .
what	One of "range", "log.range", "variance", "log.variance", "matern.correlation" or "matern.covariance".

Value

A prediction object.

Author(s)

Finn Lindgren <<Finn.Lindgren@ed.ac.uk>>

Examples

```
# Load INLA
library(INLA)

# Load 1D Poisson process data
data(Poisson2_1D)

# Take a look at the point (and frequency) data
ggplot(pts2) +
  geom_histogram(aes(x = x), binwidth = 55/20, boundary = 0, fill = NA, color = "black") +
  geom_point(aes(x), y = 0, pch = "|", cex = 4) +
  coord_fixed(ratio = 1)

# Fit an LGCP model with and SPDE component
```

```

x <- seq(0, 55, length = 20)
mesh1D <- inla.mesh.1d(x, boundary = "free")
mdl <- x ~ spde1D(map = x, model = inla.spde2.matern(mesh1D)) + Intercept
init.tutorial()
fit <- lgcp(mdl, pts2, domain = list(x = c(0,55)))

# Calculate and plot the posterior range

range = spde.posterior(fit, "spde1D", "range")
plot(range)

# Calculate and plot the posterior log range

lrange = spde.posterior(fit, "spde1D", "log.range")
plot(lrange)

# Calculate and plot the posterior variance

variance = spde.posterior(fit, "spde1D", "variance")
plot(variance)

# Calculate and plot the posterior log variance

lvariance = spde.posterior(fit, "spde1D", "log.variance")
plot(lvariance)

# Calculate and plot the posterior Matern correlation

matcor = spde.posterior(fit, "spde1D", "matern.correlation")
plot(matcor)

# Calculate and plot the posterior Matern covariance

matcov = spde.posterior(fit, "spde1D", "matern.covariance")
plot(matcov)

```

spoly

*Convert a data.frame of boundary points into a SpatialPolygons-
DataFrame*

Description

A polygon can be described as a sequence of points defining the polygon's boundary. When given such a sequence (anti clockwise!) this function creates a `SpatialPolygonsDataFrame` holding the polygon described. By default, the first two columns of data are assumed to define the x and y coordinates of the points. This behavior can be changed using the `cols` parameter, which points out the names of the columns holding the coordinates. The coordinate reference system of the

resulting spatial polygon can be set via the `crs` parameter. Posterior conversion to a different CRS is supported using the `to.crs` parameter.

Usage

```
spoly(data, cols = colnames(data)[1:2], crs = CRS(as.character(NA)),
      to.crs = NULL)
```

Arguments

<code>data</code>	A data.frame of points describing the boundary of the polygon
<code>cols</code>	Column names of the x and y coordinates within the data
<code>crs</code>	Coordinate reference system of the points
<code>to.crs</code>	Coordinate reference system for the SpatialLines output.

Value

SpatialPolygonsDataFrame

Examples

```
# Create data frame of boundary points (anti clockwise!)
pts = data.frame(x = c(1,2,1.7,1.3),
                 y = c(1,1,2,2))

# Convert to SpatialPolygonsDataFrame
pol = spoly(pts, crs = CRS(as.character(NA)))

# Plot it!
ggplot() + gg(pol)
```

stransform

Coordinate transformation for spatial objects

Description

This is a wrapper for the [spTransform](#) function provided by the `sp` package. Given a spatial object (or a list thereof) it will transform the coordinate system according to the parameter `crs`. In addition to the usual spatial objects this function is also capable of transforming [inla.mesh](#) objects that are equipped with a coordinate system.#'

Usage

```
stransform(splist, crs)
```


Arguments

splist list of Spatial* objects
 crs Coordinate reference system to change to

Value

List of Spatial* objects

Examples

```
# Load Gorilla data
data("gorillas", package = "inlabru")

# Take the mesh and transform it to latitude/longitude
tmesh = stransform(gorillas$mesh, crs = CRS("+proj=longlat"))

# Compare original and transformed mesh

multiplot(ggplot() + gg(gorillas$mesh) + ggtitle("Original mesh"),
          ggplot() + gg(tmesh) + ggtitle("Transformed mesh"))
```

summary.bru

Summary for a [bru](#) fit

Description

Takes a fitted bru object produced by bru() or lgcp() and creates various summaries from it.

Usage

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

Arguments

object An object obtained from a [bru](#) or [lgcp](#) call
 ... ignored arguments

Examples

```
# Simulate some covariates x and observations y
input.df <- data.frame(x=cos(1:10))
input.df <- within(input.df, y <- 5 + 2*x + rnorm(10, mean=0, sd=0.1))

# Fit a Gaussian likelihood model
```

```

fit <- bru(y ~ x + Intercept, "gaussian", input.df)

# Obtain summary
summary(fit)

# Alternatively, we can use the like() function to construct the likelihood:

lik = like(family = "gaussian", data = input.df)
fit <- bru(y ~ x + Intercept, lik)
summary(fit)

# An important addition to the INLA methodology is bru's ability to use
# non-linear predictors. Such a predictor can be formulated via like()'s
# \code{formula} parameter. For instance

z = 2
input.df <- within(input.df, y <- 5 + exp(z)*x + rnorm(10, mean=0, sd=0.1))
lik = like(family = "gaussian", data = input.df, formula = y ~ exp(z)*x + Intercept, E = 10000)
fit <- bru( ~ z + Intercept, lik)

# Check the result (z posterior should be around 2)
summary(fit)

```

toygroups

Simulated 1D animal group locations and group sizes

Description

This data set serves to teach the concept of modelling species that gather in groups and where the grouping behaviour depends on space.

Usage

```
data(toygroups)
```

Format

The data are a list that contains these elements:

groups: A data.frame of group locations x and size $size$

df.size: IGNORE THIS

df.intensity: A data.frame with Poisson process intensity $d.lambda$ at locations x

df.rate: A data.frame the locations x and associated rate which parameterized the exponential distribution from which the group sizes were drawn.

Examples

```

# Load the data

data("toygroups")

# The data set is a simulation of animal groups residing in a 1D space. Their
# locations in x-space are sampled from a Cox process with intensity

ggplot(toygroups$df.intensity) + geom_line(aes(x=x,y=g.lambda))

# Adding the simulated group locations to this plot we obtain

ggplot(toygroups$df.intensity) +
  geom_line(aes(x=x,y=g.lambda)) +
  geom_point(data = toygroups$groups, aes(x, y=0), pch="|")

# Each group has a size mark attached to it.
# These group sizes are sampled from an exponential distribution
# for which the rate parameter depends on the x-coordinate

ggplot(toygroups$groups) +
  geom_point(aes(x= x, y = size))

ggplot(toygroups$df.rate) +
  geom_line(aes(x,rate))

```

vertices

Vertices

Description

This is a generic function. The outcome depends on the object provided
 Vertices

Usage

```

vertices(object)

## S4 method for signature 'inla.mesh'
vertices(object)

```

Arguments

object An object for which to call the particular vertices method.

Value

The form of the value returned by vertices() depends on the class of its argument. See the documentation of the particular methods for details of what is produced by that method.

vertices.inla.mesh *Extract vertex locations from an inla.mesh*

Description

Converts the vertices of an inla.mesh object into a SpatialPointsDataFrame.

Usage

```
vertices.inla.mesh(object)
```

Arguments

object An inla.mesh object.

Value

A SpatialPointsDataFrame of mesh vertex locations. The vrt column indicates the internal vertex id.

Author(s)

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Examples

```
data("mrsea")
vrt = vertices(mrsea$mesh)
ggplot() + gg(mrsea$mesh) + gg(vrt, color = "red")
```

Index

aes, [21–23](#), [25](#), [27](#), [30](#), [31](#), [33](#)
aes_, [21–23](#), [25](#), [27](#), [30](#), [31](#), [33](#)

bincount, [3](#)
bru, [3](#), [4](#), [6–10](#), [15](#), [44](#), [48](#), [49](#), [54](#), [62](#), [65](#), [73](#)
bru.components, [5](#), [6](#)
bru.options, [5](#), [8](#), [47](#)

class, [16](#)
control.compute, [9](#)
control.inla, [9](#)
countdata1 (Poisson1_1D), [58](#)
countdata2 (Poisson2_1D), [59](#)
countdata3a (Poisson3_1D), [60](#)
countdata3b (Poisson3_1D), [60](#)
cov2_1D (Poisson2_1D), [59](#)
cprod, [9](#)
CRS, [19](#), [27](#), [30](#), [31](#), [33](#)

deltaIC, [10](#)
devel.cvmeasure, [11](#)

E_nc1 (Poisson1_1D), [58](#)
E_nc2 (Poisson2_1D), [59](#)
E_nc3a (Poisson3_1D), [60](#)
E_nc3b (Poisson3_1D), [60](#)

f, [7](#)
formula, [5](#), [49](#)

generate, [13](#), [15](#)
generate.bru, [14](#), [15](#), [62](#)
geom_line, [17](#), [19](#), [20](#), [22](#), [23](#)
geom_point, [21](#), [29](#), [31](#)
geom_polygon, [33](#)
geom_ribbon, [17](#), [22](#), [23](#)
geom_segment, [27](#)
geom_tile, [22](#), [24–26](#), [29](#), [30](#)
gg, [16](#), [17](#), [20–23](#), [25–27](#), [29–31](#), [33](#), [39](#), [40](#),
[44](#), [55](#)
gg.data.frame, [17](#), [17](#), [22](#), [23](#), [40](#)
gg.inla.mesh, [17](#), [19](#), [21](#), [40](#)
gg.inla.mesh.1d, [17](#), [20](#), [20](#), [40](#)
gg.matrix, [17](#), [22](#), [23](#), [40](#)
gg.prediction, [17](#), [22](#), [22](#), [40](#), [55](#)
gg.RasterLayer, [17](#), [24](#), [40](#)
gg.SpatialGridDataFrame, [17](#), [25](#), [27](#),
[29–31](#), [33](#), [40](#)
gg.SpatialLines, [17](#), [26](#), [27](#), [29–31](#), [33](#), [40](#)
gg.SpatialPixels, [17](#), [26](#), [27](#), [28](#), [30](#), [31](#), [33](#),
[40](#)
gg.SpatialPixelsDataFrame, [17](#), [26](#), [27](#), [29](#),
[29](#), [31](#), [33](#), [40](#)
gg.SpatialPoints, [17](#), [26](#), [27](#), [29](#), [30](#), [31](#), [33](#),
[40](#)
gg.SpatialPolygons, [17](#), [26](#), [27](#), [29–31](#), [32](#),
[40](#)
ggplot, [55](#)
globe, [34](#), [36–39](#)
glplot, [35](#), [35](#), [37–39](#)
glplot.inla.mesh, [35](#), [36](#), [36](#), [38](#), [39](#)
glplot.SpatialLines, [35–37](#), [37](#), [39](#)
glplot.SpatialPoints, [35–38](#), [38](#)
gm, [17](#), [20–23](#), [25–27](#), [29–31](#), [33](#), [39](#)
gmap, [39](#), [40](#)
gorillas, [41](#), [44](#)

init.tutorial, [43](#)
inla, [4–6](#), [8–10](#), [49](#), [54](#)
inla.mesh, [19](#), [66](#), [72](#)
inlabru, [43](#)
int, [44](#)
ipoints, [9](#), [45](#)

lambda1_1D (Poisson1_1D), [58](#)
lambda2_1D (Poisson2_1D), [59](#)
lambda3_1D (Poisson3_1D), [60](#)
lgcp, [3–5](#), [9](#), [10](#), [44](#), [47](#), [62](#), [65](#), [73](#)
like, [5](#), [48](#)

mexdolphins, [44](#), [50](#)

mrsea, 51
multiplot, 52

pixels, 53
plot.bru, 54
plot.prediction, 55
plotsample, 56
point2count, 58
Poisson1_1D, 44, 58
Poisson2_1D, 44, 59
Poisson3_1D, 60
predict, 3, 69
predict.bru, 7, 22, 23, 62
predict.inla, 64
pts1 (Poisson1_1D), 58
pts2 (Poisson2_1D), 59
pts3 (Poisson3_1D), 60

sample.lgcp, 66
seals, 44, 67
sline, 68
spatial.to.ppp, 69
SpatialPixels, 29
spde.posterior, 70
spoly, 71
spTransform, 72
stransform, 72
summary.bru, 73

toygroups, 44, 74

vertices, 75
vertices.inla.mesh-method (vertices), 75
vertices.inla.mesh, 76