Package: gstat (via r-universe)

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Title Spatial and Spatio-Temporal Geostatistical Modelling, Prediction and Simulation

Description Variogram modelling; simple, ordinary and universal point or block (co)kriging; spatio-temporal kriging; sequential Gaussian or indicator (co)simulation; variogram and variogram map plotting utility functions; supports sf and stars.

Depends R (>= 2.10)

Imports utils, stats, graphics, methods, lattice, sp (>= 0.9-72), zoo, sf (>= 0.7-2), sftime, spacetime (>= 1.2-8), stars, FNN

Suggests fields, maps, mapdata, xts, raster, future, future.apply, RColorBrewer, geoR, ggplot2

License GPL (>= 2.0)

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`coalash` *Coal ash samples from a mine in Pennsylvania*

Description

Data obtained from Gomez and Hazen (1970, Tables 19 and 20) on coal ash for the Robena Mine Property in Greene County Pennsylvania.

Usage

```
data(coalash)
```

Format

This data frame contains the following columns:

x a numeric vector; x-coordinate; reference unknown

y a numeric vector; x-coordinate; reference unknown

coalash the target variable

Note

data are also present in package fields, as coalash.

Author(s)

unknown; R version prepared by Edzer Pebesma; data obtained from http://homepage.divms.uiowa.edu/~dzimmer/spatialstats/, Dale Zimmerman's course page

References

N.A.C. Cressie, 1993, Statistics for Spatial Data, Wiley.

Gomez, M. and Hazen, K. (1970). Evaluating sulfur and ash distribution in coal seems by statistical response surface regression analysis. U.S. Bureau of Mines Report RI 7377.

see also fields manual: https://www.image.ucar.edu/GSP/Software/Fields/fields.manual.coalashEX.Krig.shtml

Examples

```
data(coalash)
summary(coalash)
```

DE_RB_2005 *Spatio-temporal data set with rural background PM10 concentrations in Germany 2005*

Description

Spatio-temporal data set with rural background PM10 concentrations in Germany 2005 (airbase v6).

Usage

```
data("DE_RB_2005")
```

Format

The format is: Formal class 'STSDF' [package "spacetime"] with 5 slots ..@ data :'data.frame': 23230 obs. of 2 variables: .. ..$ PM10 : num [1:23230] 16.7 31.7 5 22.4 26.8 ... .$ logPM10: num [1:23230] 2.82 3.46 1.61 3.11 3.29 ... ..@ index : int [1:23230, 1:2] 1 2 3 4 5 6 7 8 9 10 ... ..@ sp :Formal class 'SpatialPointsDataFrame' [package "sp"] with 5 slots .. .. ..@ data :'data.frame': 69 obs. of 9 variables: .. ..$ station_altitude : int [1:69] 8 3 700 15 35 50 343 339 45 45 ... .$ station_european_code: Factor w/ 7965 levels "AD0942A","AD0944A",..: 1991 1648 1367 2350 1113 1098 1437 2043 1741 1998 ... .$ country_iso_code : Factor w/ 39 levels "AD","AL","AT",..: 10 10 10 10 10 10 10 10 10 10 ... .$ station_start_date : Factor w/ 2409 levels "1900-01-01","1951-04-01",..: 152 1184 1577 1132 744 328 1202 1555 1148 407 ... .$ station_end_date : Factor w/ 864 levels "","1975-02-06",..: 1 1 1 579 1 1 1 1 1 1 ... .$ type_of_station : Factor w/ 5 levels "","Background",..: 2 2 2 2 2 2 2 2 2 2 ... .$ station_type_of_area : Factor w/ 4 levels "rural","suburban",..: 1 1 1 1 1 1 1 1 1 1 ... .$ street_type : Factor w/ 5 levels "","Canyon street: L/H < 1.5",..: 4 1 1 1 1 1 1 1 1 1 ... .$ annual_mean_PM10 : num [1:69] 20.9 21.8 16.5 20.3 23.3 ... .@ coords.nrs : num(0) .. .. ..@ coords : num [1:69, 1:2] 538709 545414 665711 551796 815738 ... .- attr(*, "dimnames")=List of 2 .. ..$: chr [1:69] "DESH001" "DENI063" "DEBY109" "DEUB038" ... .$: chr [1:2] "coords.x1" "coords.x2" .. .. ..@ bbox : num [1:2, 1:2] 307809 5295752 907375 6086661 .. ..- attr(*, "dimnames")=List of 2 .. ..$: chr [1:2] "coords.x1" "coords.x2" .. ..$: chr [1:2] "min" "max" .. .. ..@ proj4string:Formal class 'CRS' [package "sp"] with 1 slot .. ..@ projargs: chr "+init=epsg:32632 +proj=utm +zone=32 +datum=WGS84 +units=m +no_defs +ellps=WGS84 +towgs84=0,0,0" ..@ time :An ?xts? object on 2005-01-01/2005-12-31 containing: Data: int [1:365, 1] 5115 5116 5117 5118 5119 5120 5121 5122 5123 5124 ... - attr(*, "dimnames")=List of 2 ..$: NULL ..$: chr "..1" Indexed by objects of class: [POSIXct,POSIXt] TZ: GMT xts Attributes: NULL ..@ endTime: POSIXct[1:365], format: "2005-01-02" "2005-01-03" "2005-01-04" "2005-01-05" ...

Source

EEA, airbase v6

Examples

```
data(DE_RB_2005)
str(DE_RB_2005)
```

`estiStAni` *Estimation of the spatio-temporal anisotropy*

Description

Estimation of the spatio-temporal anisotropy without an underlying spatio-temporal model. Different methods are implemented using a linear model to predict the temporal gamma values or the ratio of the ranges of a spatial and temporal variogram model or a spatial variogram model to predict the temporal gamma values or the spatio-temporal anisotropy value as used in a metric spatio-temporal variogram.

Usage

```
estiStAni(empVgm, interval, method = "linear", spatialVgm,
          temporalVgm, s.range=NA, t.range=NA)
```

Arguments

`empVgm`	An empirical spatio-temporal variogram.
`interval`	A search interval for the optimisation of the spatio-temporal anisotropy parameter
`method`	A character string determining the method to be used (one of `linear`, `range`, `vgm` or `metric`, see below for details)
`spatialVgm`	A spatial variogram definition from the call to `vgm`. The model is optimised based on the pure spatial values in `empVgm`.
`temporalVgm`	A temporal variogram definition from the call to `vgm`. The model is optimised based on the pure temporal values in `empVgm`.
`s.range`	A spatial cutoff value applied to the empirical variogram `empVgm`.
`t.range`	A temporal cutoff value applied to the empirical variogram `empVgm`.

Details

linear A linear model is fitted to the pure spatial gamma values based on the spatial distances. An optimal scaling is searched to stretch the temporal distances such that the linear model explains best the pure temporal gamma values. This assumes (on average) a linear relationship between distance and gamma, hence it is advisable to use only those pairs of pure spatial (pure temporal) distance and gamma value that show a considerable increase (i.e. drop all values beyond the range by setting values for `s.range` and `t.range`).

range A spatial and temporal variogram model is fitted to the pure spatial and temporal gamma values respectively. The spatio-temporal anisotropy estimate is the ratio of the spatial range over the temporal range.

vgm A spatial variogram model is fitted to the pure spatial gamma values. An optimal scaling is used to stretch the temporal distances such that the spatial variogram model explains best the pure temporal gamma values.

metric A metric spatio-temporal variogram model is fitted with `joint` component according to the defined spatial variogram `spatialVgm`. The starting value of `stAni` is the mean of the `interval` parameter (see vgmST for the metric variogram definition). The spatio-temporal anisotropy as estimated in the spatio-temporal variogram is returned. Note that the parameter `interval` is only used to set the starting value. Hence, the estimate might exceed the given interval.

Value

A scalar representing the spatio-temporal anisotropy estimate.

Note

Different methods might lead to very different estimates. All but the `linear` approach are sensitive to the variogram model selection.

Author(s)

Benedikt Graeler

Examples

```
data(vv)

estiStAni(vv, c(10, 150))
estiStAni(vv, c(10, 150), "vgm", vgm(80, "Sph", 120, 20))
```

---

extractPar *Extracting parameters and their names from a spatio-temporal variogram model*

Description

All spatio-temporal variogram models have a different set of parameters. These functions extract the parameters and their names from the spatio-temporal variogram model. Note, this function is as well used to pass the parameters to the optim function. The arguments lower and upper passed to optim should follow the same structure.

Usage

```
extractPar(model)
extractParNames(model)
```

Arguments

`model`	a spatio-temporal variogram model from vgmST

Value

A named numeric vector of parameters or a vector of characters holding the parameters' names.

Author(s)

Benedikt Graeler

See Also

fit.StVariogram and vgmST

Examples

```
sumMetricModel <- vgmST("sumMetric",
                        space=vgm(30, "Sph", 200,  6),
                        time =vgm(30, "Sph",  15,  7),
                        joint=vgm(60, "Exp",  84, 22),
                        stAni=100)

extractPar(sumMetricModel)
extractParNames(sumMetricModel)
```

---

fit.lmc *Fit a Linear Model of Coregionalization to a Multivariable Sample Variogram*

Description

Fit a Linear Model of Coregionalization to a Multivariable Sample Variogram; in case of a single variogram model (i.e., no nugget) this is equivalent to Intrinsic Correlation

Usage

```
fit.lmc(v, g, model, fit.ranges = FALSE, fit.lmc = !fit.ranges,
correct.diagonal = 1.0, ...)
```

Arguments

v	multivariable sample variogram, output of variogram
g	gstat object, output of gstat
model	variogram model, output of vgm; if supplied this value is used as initial value for each fit
fit.ranges	logical; determines whether the range coefficients (excluding that of the nugget component) should be fitted; or logical vector: determines for each range parameter of the variogram model whether it should be fitted or fixed.
fit.lmc	logical; if TRUE, each coefficient matrices of partial sills is guaranteed to be positive definite

`correct.diagonal`
: multiplicative correction factor to be applied to partial sills of direct variograms only; the default value, 1.0, does not correct. If you encounter problems with singular covariance matrices during cokriging or cosimulation, you may want to try to increase this to e.g. 1.01

`...`
: parameters that get passed to fit.variogram

Value

returns an object of class `gstat`, with fitted variograms;

Note

This function does not use the iterative procedure proposed by M. Goulard and M. Voltz (Math. Geol., 24(3): 269-286; reproduced in Goovaerts' 1997 book) but uses simply two steps: first, each variogram model is fitted to a direct or cross variogram; next each of the partial sill coefficient matrices is approached by its in least squares sense closest positive definite matrices (by setting any negative eigenvalues to zero).

The argument `correct.diagonal` was introduced by experience: by zeroing the negative eigenvalues for fitting positive definite partial sill matrices, apparently still perfect correlation may result, leading to singular cokriging/cosimulation matrices. If someone knows of a more elegant way to get around this, please let me know.

Author(s)

Edzer Pebesma

See Also

variogram, vgm, fit.variogram, `demo(cokriging)`

`fit.StVariogram` *Fit a spatio-temporal sample variogram to a sample variogram*

Description

Fits a spatio-temporal variogram of a given type to spatio-temporal sample variogram.

Usage

```
fit.StVariogram(object, model, ...,  method = "L-BFGS-B",
 lower, upper, fit.method = 6, stAni=NA, wles)
```

Arguments

object	The spatio-temporal sample variogram. Typically output from variogramST
model	The desired spatio-temporal model defined through vgmST.
...	further arguments passed to optim. extractParNames provides the parameter structure of spatio-temporal variogram models that help to provide sensible upper and lower limits.
lower	Lower limits used by optim. If missing, the smallest well defined values are used (mostly near 0).
upper	Upper limits used by optim. If missing, the largest well defined values are used (mostly Inf).
method	fit method, pass to optim
fit.method	an integer between 0 and 13 determine the fitting routine (i.e. weighting of the squared residuals in the LSE). Values 0 to 6 correspond with the pure spatial version (see fit.variogram). See the details section for the meaning of the other values (partly experimental).
stAni	The spatio-temporal anisotropy that is used in the weighting. Might be missing if the desired spatio-temporal variogram model does contain a spatio-temporal anisotropy parameter (this might cause bad convergence behaviour). The default is NA and will be understood as identity (1 temporal unit = 1 spatial unit). As this only in very few cases a valid assumption, a warning is issued.
wles	Should be missing; only for backwards compatibility, wles = TRUE corresponds to fit.method = 1 and wles = FALSE corresponds to fit.method = 6.

Details

The following list summarizes the meaning of the fit.method argument which is essential a weighting of the squared residuals in the least-squares estimation. Please note, that weights based on the models gamma value might fail to converge properly due to the dependence of weights on the variogram estimate:

fit.method = 0 no fitting, however the MSE between the provided variogram model and sample variogram surface is calculated.

fit.method = 1 Number of pairs in the spatio-temporal bin: N_j

fit.method = 2 Number of pairs in the spatio-temporal bin divided by the square of the current variogram model's value: $N_j/\gamma(h_j, u_j)^2$

fit.method = 3 Same as fit.method = 1 for compatibility with fit.variogram but as well evaluated in R.

fit.method = 4 Same as fit.method = 2 for compatibility with fit.variogram but as well evaluated in R.

fit.method = 5 Reserved for REML for compatibility with fit.variogram, not yet implemented.

fit.method = 6 No weights.

fit.method = 7 Number of pairs in the spatio-temporal bin divided by the square of the bin's metric distance. If stAni is not specified, the model's parameter is used to calculate the metric distance across space and time: $N_j/(h_j^2 + \mathrm{stAni}^2 \cdot u_j^2)$

`fit.method = 8` Number of pairs in the spatio-temporal bin divided by the square of the bin's spatial distance. N_j/h_j^2. Note that the 0 distances are replaced by the smallest non-zero distances to avoid division by zero.

`fit.method = 9` Number of pairs in the spatio-temporal bin divided by the square of the bin's temporal distance. N_j/u_j^2. Note that the 0 distances are replaced by the smallest non-zero distances to avoid division by zero.

`fit.method = 10` Reciprocal of the square of the current variogram model's value: $1/\gamma(h_j, u_j)^2$

`fit.method = 11` Reciprocal of the square of the bin's metric distance. If `stAni` is not specified, the model's parameter is used to calculate the metric distance across space and time: $1/(h_j^2 + \mathrm{stAni}^2 \cdot u_j^2)$

`fit.method = 12` Reciprocal of the square of the bin's spatial distance. $1/h_j^2$. Note that the 0 distances are replaced by the smallest non-zero distances to avoid division by zero.

`fit.method = 13` Reciprocal of the square of the bin's temporal distance. $1/u_j^2$. Note that the 0 distances are replaced by the smallest non-zero distances to avoid division by zero.

See also Table 4.2 in the gstat manual for the original spatial version.

Value

Returns a spatio-temporal variogram model, as S3 class StVariogramModel. It carries the temporal and spatial unit as attributes `"temporal unit"` and `"spatial unit"` in order to allow `krigeST` to adjust for different units. The units are obtained from the provided empirical variogram. Further attributes are the optim output `"optim.output"` and the always not weighted mean squared error `"MSE"`.

Author(s)

Benedikt Graeler

See Also

`fit.variogram` for the pure spatial case. `extractParNames` helps to understand the parameter structure of spatio-temporal variogram models.

Examples

```
# separable model: spatial and temporal sill will be ignored
# and kept constant at 1-nugget respectively. A joint sill is used.
## Not run:
separableModel <- vgmST("separable",
                        method = "Nelder-Mead", # no lower & upper needed
                        space=vgm(0.9,"Exp", 123, 0.1),
                        time =vgm(0.9,"Exp", 2.9, 0.1),
                        sill=100)

data(vv)
separableModel <- fit.StVariogram(vv, separableModel,
                                  method="L-BFGS-B",
                                  lower=c(10,0,0.01,0,1),
```

```
                                    upper=c(500,1,20,1,200))
plot(vv, separableModel)

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

`fit.variogram` *Fit a Variogram Model to a Sample Variogram*

Description

Fit ranges and/or sills from a simple or nested variogram model to a sample variogram

Usage

```
fit.variogram(object, model, fit.sills = TRUE, fit.ranges = TRUE,
 fit.method = 7, debug.level = 1, warn.if.neg = FALSE, fit.kappa = FALSE)
```

Arguments

`object`	sample variogram, output of variogram
`model`	variogram model, output of vgm; see Details below for details on how `NA` values in `model` are initialised.
`fit.sills`	logical; determines whether the partial sill coefficients (including nugget variance) should be fitted; or logical vector: determines for each partial sill parameter whether it should be fitted or fixed.
`fit.ranges`	logical; determines whether the range coefficients (excluding that of the nugget component) should be fitted; or logical vector: determines for each range parameter whether it should be fitted or fixed.
`fit.method`	fitting method, used by gstat. The default method uses weights N_h/h^2 with N_h the number of point pairs and h the distance. This criterion is not supported by theory, but by practice. For other values of `fit.method`, see details.
`debug.level`	integer; set gstat internal debug level
`warn.if.neg`	logical; if TRUE a warning is issued whenever a sill value of a direct variogram becomes negative
`fit.kappa`	logical; if `TRUE`, a sequence of 0.3, 0.4,...,5 will be searched for optimal fit; alternatively another sequence can be given to this argument

Details

If any of the initial parameters of `model` are `NA`, they are given default values as follows. The range parameter is given one third of the maximum value of `object$dist`. The nugget value is given the mean value of the first three values of `object$gamma`. The partial sill is given the mean of the last five values of `object$gamma`.

Values for `fit.method` are 1: weights equal to N_j; 2: weights equal to $N_j/((gamma(h_j))^2)$; 5 (ignore, use fit.variogram.reml); 6: unweighted (OLS); 7: $N_j/(h_j^2)$.

Value

returns a fitted variogram model (of class `variogramModel`).

This is a `data.frame` with two attributes: (i) `singular` a logical attribute that indicates whether the non-linear fit converged (FALSE), or ended in a singularity (TRUE), and (ii) `SSErr` a numerical attribute with the (weighted) sum of squared errors of the fitted model. See Notes below.

Note

If fitting the range(s) is part of the job of this function, the results may well depend on the starting values, given in argument `model`, which is generally the case for non-linear regression problems. This function uses internal C code, which uses Levenberg-Marquardt.

If for a direct (i.e. not a cross) variogram a sill parameter (partial sill or nugget) becomes negative, fit.variogram is called again with this parameter set to zero, and with a FALSE flag to further fit this sill. This implies that the search does not move away from search space boundaries.

On singular model fits: If your variogram turns out to be a flat, horizontal or sloping line, then fitting a three parameter model such as the exponential or spherical with nugget is a bit heavy: there's an infinite number of possible combinations of sill and range (both very large) to fit to a sloping line. In this case, the returned, singular model may still be useful: just try and plot it. Gstat converges when the parameter values stabilize, and this may not be the case. Another case of singular model fits happens when a model that reaches the sill (such as the spherical) is fit with a nugget, and the range parameter starts, or converges to a value smaller than the distance of the second sample variogram estimate. In this case, again, an infinite number of possibilities occur essentially for fitting a line through a single (first sample variogram) point. In both cases, fixing one or more of the variogram model parameters may help you out.

The function will accept anisotropic sample variograms as input. It will fit a model for a given direction interval if the sample variogram only includes this direction. It is not possible to fit a multiple direction model to each direction of the sample variogram, in this case the model will be fitted to an average of all directions.

Author(s)

Edzer Pebesma

References

Pebesma, E.J., 2004. Multivariable geostatistics in S: the gstat package. Computers and Geosciences, 30: 683-691.

See Also

variogram, vgm

Examples

```
library(sp)
data(meuse)
coordinates(meuse) = ~x+y
vgm1 <- variogram(log(zinc)~1, meuse)
```

```
fit.variogram(vgm1, vgm(1, "Sph", 300, 1))
fit.variogram(vgm1, vgm("Sph"))

# optimize the value of kappa in a Matern model, using ugly <<- side effect:
f = function(x) attr(m.fit <<- fit.variogram(vgm1, vgm(,"Mat",nugget=NA,kappa=x)),"SSErr")
optimize(f, c(0.1, 5))
plot(vgm1, m.fit)
# best fit from the (0.3, 0.4, 0.5. ... , 5) sequence:
(m <- fit.variogram(vgm1, vgm("Mat"), fit.kappa = TRUE))
attr(m, "SSErr")
```

`fit.variogram.gls` *GLS fitting of variogram parameters*

Description

Fits variogram parameters (nugget, sill, range) to variogram cloud, using GLS (generalized least squares) fitting. Only for direct variograms.

Usage

```
fit.variogram.gls(formula, data, model, maxiter = 30,
  eps = .01, trace = TRUE, ignoreInitial = TRUE, cutoff = Inf,
  plot = FALSE)
```

Arguments

`formula`	formula defining the response vector and (possible) regressors; in case of absence of regressors, use e.g. `z~1`
`data`	object of class Spatial
`model`	variogram model to be fitted, output of `vgm`
`maxiter`	maximum number of iterations
`eps`	convergence criterium
`trace`	logical; if TRUE, prints parameter trace
`ignoreInitial`	logical; if FALSE, initial parameter are taken from model; if TRUE, initial values of model are ignored and taken from variogram cloud: nugget: `mean(y)/2`, sill: `mean(y)/2`, range `median(h0)/4` with `y` the semivariance cloud value and `h0` the distances
`cutoff`	maximum distance up to which point pairs are taken into consideration
`plot`	logical; if TRUE, a plot is returned with variogram cloud and fitted model; else, the fitted model is returned.

Value

an object of class "variogramModel"; see fit.variogram; if `plot` is TRUE, a plot is returned instead.

Note

Inspired by the code of Mihael Drinovac, which was again inspired by code from Ernst Glatzer, author of package vardiag.

Author(s)

Edzer Pebesma

References

Mueller, W.G., 1999: Least-squares fitting from the variogram cloud. Statistics and Probability Letters, 43, 93-98.

Mueller, W.G., 2007: Collecting Spatial Data. Springer, Heidelberg.

See Also

fit.variogram,

Examples

```
library(sp)
data(meuse)
coordinates(meuse) = ~x+y
## Not run:
fit.variogram.gls(log(zinc)~1, meuse[1:40,], vgm(1, "Sph", 900,1))

## End(Not run)
```

---

fit.variogram.reml *REML Fit Direct Variogram Partial Sills to Data*

Description

Fit Variogram Sills to Data, using REML (only for direct variograms; not for cross variograms)

Usage

```
fit.variogram.reml(formula, locations, data, model, debug.level = 1, set, degree = 0)
```

Arguments

formula	formula defining the response vector and (possible) regressors; in case of absence of regressors, use e.g. z~1
locations	spatial data locations; a formula with the coordinate variables in the right hand (dependent variable) side.
data	data frame where the names in formula and locations are to be found
model	variogram model to be fitted, output of vgm

debug.level	debug level; set to 65 to see the iteration trace and log likelihood
set	additional options that can be set; use set=list(iter=100) to set the max. number of iterations to 100.
degree	order of trend surface in the location, between 0 and 3

Value

an object of class "variogramModel"; see fit.variogram

Note

This implementation only uses REML fitting of sill parameters. For each iteration, an $n \times n$ matrix is inverted, with n the number of observations, so for large data sets this method becomes demanding. I guess there is much more to likelihood variogram fitting in package geoR, and probably also in nlme.

Author(s)

Edzer Pebesma

References

Christensen, R. Linear models for multivariate, Time Series, and Spatial Data, Springer, NY, 1991.

Kitanidis, P., Minimum-Variance Quadratic Estimation of Covariances of Regionalized Variables, Mathematical Geology 17 (2), 195–208, 1985

See Also

fit.variogram,

Examples

```
library(sp)
data(meuse)
fit.variogram.reml(log(zinc)~1, ~x+y, meuse, model = vgm(1, "Sph", 900,1))
```

---

fulmar *Fulmaris glacialis data*

Description

Airborne counts of Fulmaris glacialis during the Aug/Sept 1998 and 1999 flights on the Dutch (Netherlands) part of the North Sea (NCP, Nederlands Continentaal Plat).

Usage

```
data(fulmar)
```

Format

This data frame contains the following columns:

year year of measurement: 1998 or 1999

x x-coordinate in UTM zone 31

y y-coordinate in UTM zone 31

depth sea water depth, in m

coast distance to coast of the Netherlands, in km.

fulmar observed density (number of birds per square km)

Author(s)

Dutch National Institute for Coastal and Marine Management (RIKZ)

See Also

ncp.grid

E.J. Pebesma, R.N.M. Duin, P.A. Burrough, 2005. Mapping Sea Bird Densities over the North Sea: Spatially Aggregated Estimates and Temporal Changes. Environmetrics 16, (6), p 573-587.

Examples

```
data(fulmar)
summary(fulmar)
## Not run:
demo(fulmar)

## End(Not run)
```

---

get.contr *Calculate contrasts from multivariable predictions*

Description

Given multivariable predictions and prediction (co)variances, calculate contrasts and their (co)variance

Usage

```
get.contr(data, gstat.object, X, ids = names(gstat.object$data))
```

Arguments

`data`	data frame, output of predict
`gstat.object`	object of class `gstat`, used to extract ids; may be missing if `ids` is used
`X`	contrast vector or matrix; the number of variables in `gstat.object` should equal the number of elements in `X` if `X` is a vector, or the number of rows in `X` if `X` is a matrix.
`ids`	character vector with (selection of) id names, present in data

Details

From data, we can extract the $n \times 1$ vector with multivariable predictions, say y, and its $n \times n$ covariance matrix V. Given a contrast matrix in X, this function computes the contrast vector $C=X'y$ and its variance $Var(C)=X'V X$.

Value

a data frame containing for each row in `data` the generalized least squares estimates (named beta.1, beta.2, ...), their variances (named var.beta.1, var.beta.2, ...) and covariances (named cov.beta.1.2, cov.beta.1.3, ...)

Author(s)

Edzer Pebesma

See Also

predict

---

gstat *Create gstat objects, or subset it*

Description

Function that creates gstat objects; objects that hold all the information necessary for univariate or multivariate geostatistical prediction (simple, ordinary or universal (co)kriging), or its conditional or unconditional Gaussian or indicator simulation equivalents. Multivariate gstat object can be subsetted.

Usage

```
gstat(g, id, formula, locations, data, model = NULL, beta,
 nmax = Inf, nmin = 0, omax = 0, maxdist = Inf, force = FALSE,
 dummy = FALSE, set, fill.all = FALSE,
 fill.cross = TRUE, variance = "identity", weights = NULL, merge,
 degree = 0, vdist = FALSE, lambda = 1.0)
## S3 method for class 'gstat'
print(x, ...)
```

Arguments

`g`	gstat object to append to; if missing, a new gstat object is created
`id`	identifier of new variable; if missing, `varn` is used with `n` the number for this variable. If a cross variogram is entered, `id` should be a vector with the two `id` values , e.g. `c("zn", "cd")`, further only supplying arguments `g` and `model`. It is advisable not to use expressions, such as `log(zinc)`, as identifiers, as this may lead to complications later on.

formula	formula that defines the dependent variable as a linear model of independent variables; suppose the dependent variable has name z, for ordinary and simple kriging use the formula z~1; for simple kriging also define beta (see below); for universal kriging, suppose z is linearly dependent on x and y, use the formula z~x+y
locations	formula with only independent variables that define the spatial data locations (coordinates), e.g. ~x+y; if data has a coordinates method to extract its coordinates this argument can be ignored (see package sp for classes for point or grid data).
data	data frame; contains the dependent variable, independent variables, and locations.
model	variogram model for this id; defined by a call to vgm; see argument id to see how cross variograms are entered
beta	for simple kriging (and simulation based on simple kriging): vector with the trend coefficients (including intercept); if no independent variables are defined the model only contains an intercept and this should be the expected value; for cross variogram computations: mean parameters to be used instead of the OLS estimates
nmax	for local kriging: the number of nearest observations that should be used for a kriging prediction or simulation, where nearest is defined in terms of the space of the spatial locations
nmin	for local kriging: if the number of nearest observations within distance maxdist is less than nmin, a missing value will be generated, unless force==TRUE; see maxdist
omax	maximum number of observations to select per octant (3D) or quadrant (2D); only relevant if maxdist has been defined as well
maxdist	for local kriging: only observations within a distance of maxdist from the prediction location are used for prediction or simulation; if combined with nmax, both criteria apply
force	for local kriging, force neighbourhood selection: in case nmin is given, search beyond maxdist until nmin neighbours are found. A missing value is returned if this is not possible.
dummy	logical; if TRUE, consider this data as a dummy variable (only necessary for unconditional simulation)
set	named list with optional parameters to be passed to gstat (only set commands of gstat are allowed, and not all of them may be relevant; see the manual for gstat stand-alone, URL below)
x	gstat object to print
fill.all	logical; if TRUE, fill all of the direct variogram and, depending on the value of fill.cross also all cross variogram model slots in g with the given variogram model
fill.cross	logical; if TRUE, fill all of the cross variograms, if FALSE fill only all direct variogram model slots in g with the given variogram model (only if fill.all is used)

variance	character; variance function to transform to non-stationary covariances; "identity" does not transform, other options are "mu" (Poisson) and "mu(1-mu)" (binomial)
weights	numeric vector; if present, covariates are present, and variograms are missing weights are passed to OLS prediction routines resulting in WLS; if variograms are given, weights should be 1/variance, where variance specifies location-specific measurement error; see references section below
merge	either character vector of length 2, indicating two ids that share a common mean; the more general gstat merging of any two coefficients across variables is obtained when a list is passed, with each element a character vector of length 4, in the form `c("id1", 1,"id2", 2)`. This merges the first parameter for variable `id1` to the second of variable `id2`.
degree	order of trend surface in the location, between 0 and 3
vdist	logical; if TRUE, instead of Euclidian distance variogram distance is used for selecting the nmax nearest neighbours, after observations within distance maxdist (Euclidian/geographic) have been pre-selected
lambda	test feature; doesn't do anything (yet)
...	arguments that are passed to the printing of variogram models only

Details

to print the full contents of the object `g` returned, use `as.list(g)` or `print.default(g)`

Value

an object of class `gstat`, which inherits from `list`. Its components are:

data	list; each element is a list with the `formula`, `locations`, `data`, `nvars`, `beta`, etc., for a variable
model	list; each element contains a variogram model; names are those of the elements of `data`; cross variograms have names of the pairs of data elements, separated by a `.` (e.g.: `var1.var2`
)	
set	list; named list, corresponding to set `name=value`; gstat commands (look up the set command in the gstat manual for a full list)

Note

The function currently copies the data objects into the gstat object, so this may become a large object. I would like to copy only the name of the data frame, but could not get this to work. Any help is appreciated.

Subsetting (see examples) is done using the `id`'s of the variables, or using numeric subsets. Subsetted gstat objects only contain cross variograms if (i) the original gstat object contained them and (ii) the order of the subset indexes increases, numerically, or given the order they have in the gstat object.

The merge item may seem obscure. Still, for colocated cokriging, it is needed. See texts by Goovaerts, Wackernagel, Chiles and Delfiner, or look for standardised ordinary kriging in the 1992 Deutsch and Journel or Isaaks and Srivastava. In these cases, two variables share a common mean parameter. Gstat generalises this case: any two variables may share any of the regression coefficients; allowing for instance analysis of covariance models, when variograms were left out (see e.g. R. Christensen's "Plane answers" book on linear models). The tests directory of the package contains examples in file merge.R. There is also `demo(pcb)` which merges slopes across years, but with year-dependent intercept.

Author(s)

Edzer Pebesma

References

Pebesma, E.J., 2004. Multivariable geostatistics in S: the gstat package. Computers and Geosciences, 30: 683-691.

for kriging with known, varying measurement errors (`weights`), see e.g. Delhomme, J.P. Kriging in the hydrosciences. Advances in Water Resources, 1(5):251-266, 1978; see also the section Kriging with known measurement errors in the gstat user's manual.

See Also

predict, krige

Examples

```
library(sp)
data(meuse)
coordinates(meuse) = ~x+y
# let's do some manual fitting of two direct variograms and a cross variogram
g <- gstat(id = "ln.zinc", formula = log(zinc)~1, data = meuse)
g <- gstat(g, id = "ln.lead", formula = log(lead)~1, data = meuse)
# examine variograms and cross variogram:
plot(variogram(g))
# enter direct variograms:
g <- gstat(g, id = "ln.zinc", model = vgm(.55, "Sph", 900, .05))
g <- gstat(g, id = "ln.lead", model = vgm(.55, "Sph", 900, .05))
# enter cross variogram:
g <- gstat(g, id = c("ln.zinc", "ln.lead"), model = vgm(.47, "Sph", 900, .03))
# examine fit:
plot(variogram(g), model = g$model, main = "models fitted by eye")
# see also demo(cokriging) for a more efficient approach
g["ln.zinc"]
g["ln.lead"]
g[c("ln.zinc", "ln.lead")]
g[1]
g[2]

# Inverse distance interpolation with inverse distance power set to .5:
# (kriging variants need a variogram model to be specified)
```

```
data(meuse.grid)
gridded(meuse.grid) = ~x+y
meuse.gstat <- gstat(id = "zinc", formula = zinc ~ 1, data = meuse,
 nmax = 7, set = list(idp = .5))
meuse.gstat
z <- predict(meuse.gstat, meuse.grid)
spplot(z["zinc.pred"])
# see demo(cokriging) and demo(examples) for further examples,
# and the manuals for predict and image

# local universal kriging
gmeuse <- gstat(id = "log_zinc", formula = log(zinc)~sqrt(dist), data = meuse)
# variogram of residuals
vmeuse.res <- fit.variogram(variogram(gmeuse), vgm(1, "Exp", 300, 1))
# prediction from local neighbourhoods within radius of 170 m or at least 10 points
gmeuse <- gstat(id = "log_zinc", formula = log(zinc)~sqrt(dist),
 data = meuse, maxdist=170, nmin=10, force=TRUE, model=vmeuse.res)
predmeuse <- predict(gmeuse, meuse.grid)
spplot(predmeuse)
```

---

hscat *Produce h-scatterplot*

Description

Produces h-scatterplots, where point pairs having specific separation distances are plotted. This function is a wrapper around xyplot.

Usage

```
hscat(formula, data, breaks, pch = 3, cex = .6, mirror = FALSE,
 variogram.alpha = 0, as.table = TRUE,...)
```

Arguments

formula	specifies the dependent variable
data	data where the variable in formula is resolved
breaks	distance class boundaries
pch	plotting symbol
cex	plotting symbol size
mirror	logical; duplicate all points mirrored along x=y? (note that correlations are those of the points plotted)
variogram.alpha	parameter to be passed as alpha parameter to variogram; if alpha is specified it will only affect xyplot by being passed through ...
as.table	logical; if TRUE, panels plot top-to-bottom
...	parameters, passed to variogram and xyplot

Value

an object of class trellis; normally the h scatter plot

Note

Data pairs are plotted once, so the h-scatterplot are not symmetric.

Author(s)

Edzer Pebesma

References

Pebesma, E.J., 2004. Multivariable geostatistics in S: the gstat package. Computers and Geosciences, 30: 683-691.

Examples

```
library(sp)
data(meuse)
coordinates(meuse) = ~x+y
hscat(log(zinc)~1, meuse, c(0, 80, 120, 250, 500, 1000))
```

---

image *Image Gridded Coordinates in Data Frame*

Description

Image gridded data, held in a data frame, keeping the right aspect ratio for axes, and the right cell shape

Usage

```
## S3 method for class 'data.frame'
image(x, zcol = 3, xcol = 1, ycol = 2, asp = 1, ...)
xyz2img(xyz, zcol = 3, xcol = 1, ycol = 2, tolerance = 10 * .Machine$double.eps)
```

Arguments

x	data frame (or matrix) with x-coordinate, y-coordinate, and z-coordinate in its columns
zcol	column number or name of z-variable
xcol	column number or name of x-coordinate
ycol	column number or name of y-coordinate
asp	aspect ratio for the x and y axes
...	arguments, passed to image.default

xyz	data frame (same as x)
tolerance	maximum allowed deviation for coordinats from being exactly on a regularly spaced grid

Value

image.data.frame plots an image from gridded data, organized in arbritrary order, in a data frame. It uses xyz2img and image.default for this. In the S-Plus version, xyz2img tries to make an image object with a size such that it will plot with an equal aspect ratio; for the R version, image.data.frame uses the asp=1 argument to guarantee this.

xyz2img returns a list with components: z, a matrix containing the z-values; x, the increasing coordinates of the rows of z; y, the increasing coordinates of the columns of z. This list is suitable input to image.default.

Note

I wrote this function before I found out about levelplot, a Lattice/Trellis function that lets you control the aspect ratio by the aspect argument, and that automatically draws a legend, and therefore I now prefer levelplot over image. Plotting points on a levelplots is probably done with providing a panel function and using lpoints.

(for S-Plus only –) it is hard (if not impossible) to get exactly right cell shapes (e.g., square for a square grid) without altering the size of the plotting region, but this function tries hard to do so by extending the image to plot in either x- or y-direction. The larger the grid, the better the approximation. Geographically correct images can be obtained by modifiying par("pin"). Read the examples, image a 2 x 2 grid, and play with par("pin") if you want to learn more about this.

Author(s)

Edzer Pebesma

Examples

```
library(sp)
data(meuse)
data(meuse.grid)
g <- gstat(formula=log(zinc)~1,locations=~x+y,data=meuse,model=vgm(1,"Exp",300))
x <- predict(g, meuse.grid)
image(x, 4, main="kriging variance and data points")
points(meuse$x, meuse$y, pch = "+")
```

---

jura *Jura data set*

Description

The jura data set from Pierre Goovaerts' book (see references below). It contains four `data.frames`: prediction.dat, validation.dat and transect.dat and juragrid.dat, and three `data.frames` with consistently coded land use and rock type factors, as well as geographic coordinates. The examples below show how to transform these into spatial (sp) objects in a local coordinate system and in geographic coordinates, and how to transform to metric coordinate reference systems.

Usage

```
data(jura)
```

Format

The `data.frames` prediction.dat and validation.dat contain the following fields:

Xloc X coordinate, local grid km

Yloc Y coordinate, local grid km

Landuse see book and below

Rock see book and below

Cd mg cadmium kg^{-1} topsoil

Co mg cobalt kg^{-1} topsoil

Cr mg chromium kg^{-1} topsoil

Cu mg copper kg^{-1} topsoil

Ni mg nickel kg^{-1} topsoil

Pb mg lead kg^{-1} topsoil

Zn mg zinc kg^{-1} topsoil

The `data.frame` juragrid.dat only has the first four fields. In addition the `data.frames` jura.pred, jura.val and jura.grid also have inserted third and fourth fields giving geographic coordinates:

long Longitude, WGS84 datum

lat Latitude, WGS84 datum

Note

The points data sets were obtained from http://home.comcast.net/~pgoovaerts/book.html, which seems to be no longer available; the grid data were kindly provided by Pierre Goovaerts.

The following codes were used to convert `prediction.dat` and `validation.dat` to `jura.pred` and `jura.val` (see examples below):

Rock Types: 1: Argovian, 2: Kimmeridgian, 3: Sequanian, 4: Portlandian, 5: Quaternary.

Land uses: 1: Forest, 2: Pasture (Weide(land), Wiese, Grasland), 3: Meadow (Wiese, Flur, Matte, Anger), 4: Tillage (Ackerland, bestelltes Land)

Points 22 and 100 in the validation set (`validation.dat[c(22,100),]`) seem not to lie exactly on the grid originally intended, but are kept as such to be consistent with the book.

Georeferencing was based on two control points in the Swiss grid system shown as Figure 1 of Atteia et al. (see above) and further points digitized on the tentatively georeferenced scanned map. RMSE 2.4 m. Location of points in the field was less precise.

Author(s)

Data preparation by David Rossiter (dgr2@cornell.edu) and Edzer Pebesma; georeferencing by David Rossiter

References

Goovaerts, P. 1997. Geostatistics for Natural Resources Evaluation. Oxford Univ. Press, New-York, 483 p. Appendix C describes (and gives) the Jura data set.

Atteia, O., Dubois, J.-P., Webster, R., 1994, Geostatistical analysis of soil contamination in the Swiss Jura: Environmental Pollution 86, 315-327

Webster, R., Atteia, O., Dubois, J.-P., 1994, Coregionalization of trace metals in the soil in the Swiss Jura: European Journal of Soil Science 45, 205-218

Examples

```
data(jura)
summary(prediction.dat)
summary(validation.dat)
summary(transect.dat)
summary(juragrid.dat)

# the following commands were used to create objects with factors instead
# of the integer codes for Landuse and Rock:
## Not run:
  jura.pred = prediction.dat
  jura.val = validation.dat
  jura.grid = juragrid.dat

  jura.pred$Landuse = factor(prediction.dat$Landuse,
 labels=levels(juragrid.dat$Landuse))
  jura.pred$Rock = factor(prediction.dat$Rock,
 labels=levels(juragrid.dat$Rock))
  jura.val$Landuse = factor(validation.dat$Landuse,
 labels=levels(juragrid.dat$Landuse))
  jura.val$Rock = factor(validation.dat$Rock,
 labels=levels(juragrid.dat$Rock))

## End(Not run)

# the following commands convert data.frame objects into spatial (sp) objects
#   in the local grid:
require(sp)
coordinates(jura.pred) = ~Xloc+Yloc
coordinates(jura.val) = ~Xloc+Yloc
coordinates(jura.grid) = ~Xloc+Yloc
gridded(jura.grid) = TRUE

# the following commands convert the data.frame objects into spatial (sp) objects
#   in WGS84 geographic coordinates
# example is given only for jura.pred, do the same for jura.val and jura.grid
# EPSG codes can be found by searching make_EPSG()
```

```
jura.pred <- as.data.frame(jura.pred)
coordinates(jura.pred) = ~ long + lat
proj4string(jura.pred) = CRS("+init=epsg:4326")
```

---

krige *Simple, Ordinary or Universal, global or local, Point or Block Kriging, or simulation.*

Description

Function for simple, ordinary or universal kriging (sometimes called external drift kriging), kriging in a local neighbourhood, point kriging or kriging of block mean values (rectangular or irregular blocks), and conditional (Gaussian or indicator) simulation equivalents for all kriging varieties, and function for inverse distance weighted interpolation. For multivariable prediction, see gstat and predict

Usage

```
krige(formula, locations, ...)
krige.locations(formula, locations, data, newdata, model, ..., beta, nmax
= Inf, nmin = 0, omax = 0, maxdist = Inf, block, nsim = 0, indicators = FALSE,
na.action = na.pass, debug.level = 1)
krige.spatial(formula, locations, newdata, model, ..., beta, nmax
= Inf, nmin = 0, omax = 0, maxdist = Inf, block, nsim = 0, indicators = FALSE,
na.action = na.pass, debug.level = 1)
krige0(formula, data, newdata, model, beta, y, ..., computeVar = FALSE,
 fullCovariance = FALSE)
idw(formula, locations, ...)
idw.locations(formula, locations, data, newdata, nmax = Inf,
 nmin = 0, omax = 0, maxdist = Inf, block, na.action = na.pass, idp = 2.0,
 debug.level = 1)
idw.spatial(formula, locations, newdata, nmax = Inf, nmin = 0,
    omax = 0, maxdist = Inf, block = numeric(0), na.action = na.pass, idp = 2.0,
 debug.level = 1)
idw0(formula, data, newdata, y, idp = 2.0)
```

Arguments

formula	formula that defines the dependent variable as a linear model of independent variables; suppose the dependent variable has name z, for ordinary and simple kriging use the formula z~1; for simple kriging also define beta (see below); for universal kriging, suppose z is linearly dependent on x and y, use the formula z~x+y
locations	object of class Spatial or sf, or (deprecated) formula defines the spatial data locations (coordinates) such as ~x+y
data	data frame: should contain the dependent variable, independent variables, and coordinates, should be missing if locations contains data.

newdata	object of class Spatial, sf or stars with prediction/simulation locations; should contain attributes with the independent variables (if present).
model	variogram model of dependent variable (or its residuals), defined by a call to vgm or fit.variogram; for krige0 also a user-supplied covariance function is allowed (see example below)
beta	for simple kriging (and simulation based on simple kriging): vector with the trend coefficients (including intercept); if no independent variables are defined the model only contains an intercept and beta should be the simple kriging mean
nmax	for local kriging: the number of nearest observations that should be used for a kriging prediction or simulation, where nearest is defined in terms of the space of the spatial locations. By default, all observations are used
nmin	for local kriging: if the number of nearest observations within distance maxdist is less than nmin, a missing value will be generated; see maxdist
omax	see gstat
maxdist	for local kriging: only observations within a distance of maxdist from the prediction location are used for prediction or simulation; if combined with nmax, both criteria apply
block	block size; a vector with 1, 2 or 3 values containing the size of a rectangular in x-, y- and z-dimension respectively (0 if not set), or a data frame with 1, 2 or 3 columns, containing the points that discretize the block in the x-, y- and z-dimension to define irregular blocks relative to (0,0) or (0,0,0)—see also the details section of predict. By default, predictions or simulations refer to the support of the data values.
nsim	integer; if set to a non-zero value, conditional simulation is used instead of kriging interpolation. For this, sequential Gaussian or indicator simulation is used (depending on the value of indicators), following a single random path through the data.
indicators	logical, only relevant if nsim is non-zero; if TRUE, use indicator simulation; else use Gaussian simulation
na.action	function determining what should be done with missing values in 'newdata'. The default is to predict 'NA'. Missing values in coordinates and predictors are both dealt with.
debug.level	debug level, passed to predict; use -1 to see progress in percentage, and 0 to suppress all printed information
...	for krige: arguments that will be passed to gstat; for krige0: arguments that will be passe to model
idp	numeric; specify the inverse distance weighting power
y	matrix; to krige multiple fields in a single step, pass data as columns of matrix y. This will ignore the value of the response in formula.
computeVar	logical; if TRUE, prediction variances will be returned
fullCovariance	logical; if FALSE a vector with prediction variances will be returned, if TRUE the full covariance matrix of all predictions will be returned

Details

Function krige is a simple wrapper method around gstat and predict for univariate kriging prediction and conditional simulation methods available in gstat. For multivariate prediction or simulation, or for other interpolation methods provided by gstat (such as inverse distance weighted interpolation or trend surface interpolation) use the functions gstat and predict directly.

Function idw performs just as krige without a model being passed, but allows direct specification of the inverse distance weighting power. Don't use with predictors in the formula.

For further details, see predict.

Value

if locations is not a formula, object of the same class as newdata (deriving from Spatial); else a data frame containing the coordinates of newdata. Attributes columns contain prediction and prediction variance (in case of kriging) or the abs(nsim) columns of the conditional Gaussian or indicator simulations

krige0 and idw0 are alternative functions with reduced functionality and larger memory requirements; they return numeric vectors (or matrices, in case of multiple dependent) with predicted values only; in case computeVar is TRUE, a list with elements pred and var is returned, containing predictions, and (co)variances (depending on argument fullCovariance).

Methods

formula = "formula", locations = "formula" locations specifies which coordinates in data refer to spatial coordinates

formula = "formula", locations = "Spatial" Object locations knows about its own spatial locations

formula = "formula", locations = "NULL" used in case of unconditional simulations; newdata needs to be of class Spatial

Note

Daniel G. Krige is a South African scientist who was a mining engineer when he first used generalised least squares prediction with spatial covariances in the 50's. George Matheron coined the term kriging in the 60's for the action of doing this, although very similar approaches had been taken in the field of meteorology. Beside being Krige's name, I consider "krige" to be to "kriging" what "predict" is to "prediction".

Author(s)

Edzer Pebesma

References

N.A.C. Cressie, 1993, Statistics for Spatial Data, Wiley.

Pebesma, E.J., 2004. Multivariable geostatistics in S: the gstat package. Computers and Geosciences, 30: 683-691.

See Also

gstat, predict

Examples

```
library(sp)
data(meuse)
coordinates(meuse) = ~x+y
data(meuse.grid)
gridded(meuse.grid) = ~x+y
m <- vgm(.59, "Sph", 874, .04)
# ordinary kriging:
x <- krige(log(zinc)~1, meuse, meuse.grid, model = m)
spplot(x["var1.pred"], main = "ordinary kriging predictions")
spplot(x["var1.var"],  main = "ordinary kriging variance")
# simple kriging:
x <- krige(log(zinc)~1, meuse, meuse.grid, model = m, beta = 5.9)
# residual variogram:
m <- vgm(.4, "Sph", 954, .06)
# universal block kriging:
x <- krige(log(zinc)~x+y, meuse, meuse.grid, model = m, block = c(40,40))
spplot(x["var1.pred"], main = "universal kriging predictions")

# krige0, using user-defined covariance function and multiple responses in y:
# exponential variogram with range 500, defined as covariance function:
v = function(x, y = x) { exp(-spDists(coordinates(x),coordinates(y))/500) }
# krige two variables in a single pass (using 1 covariance model):
y = cbind(meuse$zinc,meuse$copper,meuse$lead,meuse$cadmium)
x <- krige0(zinc~1, meuse, meuse.grid, v, y = y)
meuse.grid$zinc = x[,1]
spplot(meuse.grid["zinc"], main = "zinc")
meuse.grid$copper = x[,2]
spplot(meuse.grid["copper"], main = "copper")

# the following has NOTHING to do with kriging, but --
# return the median of the nearest 11 observations:
x = krige(zinc~1, meuse, meuse.grid, set = list(method = "med"), nmax = 11)
# get 25%- and 75%-percentiles of nearest 11 obs, as prediction and variance:
x = krige(zinc~1, meuse, meuse.grid, nmax = 11,
 set = list(method = "med", quantile = 0.25))
# get diversity (# of different values) and mode from 11 nearest observations:
x = krige(zinc~1, meuse, meuse.grid, nmax = 11, set = list(method = "div"))
```

---

krige.cv *(co)kriging cross validation, n-fold or leave-one-out*

Description

Cross validation functions for simple, ordinary or universal point (co)kriging, kriging in a local neighbourhood.

Usage

```
gstat.cv(object, nfold, remove.all = FALSE, verbose = interactive(),
 all.residuals = FALSE, ...)
krige.cv(formula, locations, ...)
krige.cv.locations(formula, locations, data, model = NULL, ..., beta = NULL,
 nmax = Inf, nmin = 0, maxdist = Inf, nfold = nrow(data),
 verbose = interactive(), debug.level = 0)
krige.cv.spatial(formula, locations, model = NULL, ..., beta = NULL,
 nmax = Inf, nmin = 0, maxdist = Inf, nfold = nrow(locations),
 verbose = interactive(), debug.level = 0)
```

Arguments

`object`	object of class gstat; see function gstat
`nfold`	integer; if larger than 1, then apply n-fold cross validation; if `nfold` equals `nrow(data)` (the default), apply leave-one-out cross validation; if set to e.g. 5, five-fold cross validation is done. To specify the folds, pass an integer vector of length `nrow(data)` with fold indexes.
`remove.all`	logical; if TRUE, remove observations at cross validation locations not only for the first, but for all subsequent variables as well
`verbose`	logical; if FALSE, progress bar is suppressed
`all.residuals`	logical; if TRUE, residuals for all variables are returned instead of for the first variable only
`...`	other arguments that will be passed to predict in case of `gstat.cv`, or to gstat in case of `krige.cv`
`formula`	formula that defines the dependent variable as a linear model of independent variables; suppose the dependent variable has name `z`, for ordinary and simple kriging use the formula `z~1`; for simple kriging also define `beta` (see below); for universal kriging, suppose `z` is linearly dependent on `x` and `y`, use the formula `z~x+y`
`locations`	data object deriving from class `Spatial` or `sf`
`data`	data frame (deprecated); should contain the dependent variable, independent variables, and coordinates; only to be provided if `locations` is a formula
`model`	variogram model of dependent variable (or its residuals), defined by a call to vgm or fit.variogram
`beta`	only for simple kriging (and simulation based on simple kriging); vector with the trend coefficients (including intercept); if no independent variables are defined the model only contains an intercept and this should be the simple kriging mean
`nmax`	for local kriging: the number of nearest observations that should be used for a kriging prediction or simulation, where nearest is defined in terms of the space of the spatial locations. By default, all observations are used
`nmin`	for local kriging: if the number of nearest observations within distance `maxdist` is less than `nmin`, a missing value will be generated; see maxdist

maxdist	for local kriging: only observations within a distance of maxdist from the prediction location are used for prediction or simulation; if combined with nmax, both criteria apply
debug.level	print debugging information; 0 suppresses debug information

Details

Leave-one-out cross validation (LOOCV) visits a data point, and predicts the value at that location by leaving out the observed value, and proceeds with the next data point. (The observed value is left out because kriging would otherwise predict the value itself.) N-fold cross validation makes a partitions the data set in N parts. For all observation in a part, predictions are made based on the remaining N-1 parts; this is repeated for each of the N parts. N-fold cross validation may be faster than LOOCV.

Value

data frame containing the coordinates of data or those of the first variable in object, and columns of prediction and prediction variance of cross validated data points, observed values, residuals, zscore (residual divided by kriging standard error), and fold.

If all.residuals is true, a data frame with residuals for all variables is returned, without coordinates.

Methods

formula = "formula", locations = "formula" locations specifies which coordinates in data refer to spatial coordinates

formula = "formula", locations = "Spatial" Object locations knows about its own spatial locations

Note

Leave-one-out cross validation seems to be much faster in plain (stand-alone) gstat, apparently quite a bit of the effort is spent moving data around from R to gstat.

Author(s)

Edzer Pebesma

See Also

krige, gstat, predict

Examples

```
library(sp)
data(meuse)
coordinates(meuse) <- ~x+y
m <- vgm(.59, "Sph", 874, .04)
# five-fold cross validation:
x <- krige.cv(log(zinc)~1, meuse, m, nmax = 40, nfold=5)
```

```
bubble(x, "residual", main = "log(zinc): 5-fold CV residuals")

# multivariable; thanks to M. Rufino:
meuse.g <- gstat(id = "zn", formula = log(zinc) ~ 1, data = meuse)
meuse.g <- gstat(meuse.g, "cu", log(copper) ~ 1, meuse)
meuse.g <- gstat(meuse.g, model = vgm(1, "Sph", 900, 1), fill.all = TRUE)
x <- variogram(meuse.g, cutoff = 1000)
meuse.fit = fit.lmc(x, meuse.g)
out = gstat.cv(meuse.fit, nmax = 40, nfold = 5)
summary(out)
out = gstat.cv(meuse.fit, nmax = 40, nfold = c(rep(1,100), rep(2,55)))
summary(out)
# mean error, ideally 0:
mean(out$residual)
# MSPE, ideally small
mean(out$residual^2)
# Mean square normalized error, ideally close to 1
mean(out$zscore^2)
# correlation observed and predicted, ideally 1
cor(out$observed, out$observed - out$residual)
# correlation predicted and residual, ideally 0
cor(out$observed - out$residual, out$residual)
```

`krigeSimCE` *Simulation based on circulant embedding*

Description

Simulating a conditional/unconditional Gaussian random field via kriging and circulant embedding

Usage

```
krigeSimCE(formula, data, newdata, model, n = 1, ext = 2)
```

Arguments

`formula`	the formula of the kriging predictor
`data`	spatial data frame that conditions the simulation
`newdata`	locations in space where the Gaussian random field shall be simulated
`model`	a vgm model that defines the spatial covariance structure
`n`	number of simulations
`ext`	extension factor of the circulant embedding, defaults to 2

Value

A spatial data frame as defined in `newdata` with `n` simulations.

Author(s)

Benedikt Graeler

References

Davies, Tilman M., and David Bryant: "On circulant embedding for Gaussian random fields in R." Journal of Statistical Software 55.9 (2013): 1-21. See i.e. the supplementary files at (retrieved 2018-05-25): https://www.jstatsoft.org/index.php/jss/article/downloadSuppFile/v055i09/v55i09.R

See Also

krigeSTSimTB

Examples

```
# see demo('circEmbeddingMeuse')
```

---

krigeST *Ordinary global Spatio-Temporal Kriging*

Description

Function for ordinary global and local and trans Gaussian spatio-temporal kriging on point support

Usage

```
krigeST(formula, data, newdata, modelList, beta, y, ...,
        nmax = Inf, stAni = NULL,
        computeVar = FALSE, fullCovariance = FALSE,
        bufferNmax=2, progress=TRUE)
krigeSTTg(formula, data, newdata, modelList, y, nmax=Inf, stAni=NULL,
                      bufferNmax=2, progress=TRUE, lambda = 0)
```

Arguments

formula	formula that defines the dependent variable as a linear model of independent variables; suppose the dependent variable has name z, for ordinary and simple kriging use the formula z~1; for simple kriging also define beta (see below); for universal kriging, suppose z is linearly dependent on x and y, use the formula z~x+y
data	ST object: should contain the dependent variable and independent variables.
newdata	ST object with prediction/simulation locations in space and time; should contain attribute columns with the independent variables (if present).

modelList	object of class StVariogramModel, created by vgmST - see below or the function vgmAreaST for area-to-point kriging. For the general kriging case: a list with named elements: space, time and/or joint depending on the spatio-temporal covariance family, and an entry stModel. Currently implemented families that may be used for stModel are separable, productSum, metric, sumMetric and simpleSumMetric. See the examples section in fit.StVariogram or variogramSurface for details on how to define spatio-temporal covariance models. krigeST will look for a "temporal unit" attribute in the provided modelList in order to adjust the temporal scales.
y	matrix; to krige multiple fields in a single step, pass data as columns of matrix y. This will ignore the value of the response in formula.
beta	The (known) mean for simple kriging.
nmax	The maximum number of neighbouring locations for a spatio-temporal local neighbourhood
stAni	a spatio-temporal anisotropy scaling assuming a metric spatio-temporal space. Used only for the selection of the closest neighbours. This scaling needs only to be provided in case the model does not have a stAni parameter, or if a different one should be used for the neighbourhood selection. Mind the correct spatial unit. Currently, no coordinate conversion is made for the neighbourhood selection (i.e. Lat and Lon require a spatio-temporal anisotropy scaling in degrees per second).
...	further arguments used for instance to pass the model into vgmAreaST for area-to-point kriging
computeVar	logical; if TRUE, prediction variances will be returned
fullCovariance	logical; if FALSE a vector with prediction variances will be returned, if TRUE the full covariance matrix of all predictions will be returned
bufferNmax	factor with which nmax is multiplied for an extended search radius (default=2). Set to 1 for no extension of the search radius.
progress	whether a progress bar shall be printed for local spatio-temporal kriging; default=TRUE
lambda	The value of lambda used in the box-cox transformation.

Details

Function krigeST is a R implementation of the kriging function from gstat using spatio-temporal covariance models following the implementation of krige0. Function krigeST offers some particular methods for ordinary spatio-temporal (ST) kriging. In particular, it does not support block kriging or kriging in a distance-based neighbourhood, and does not provide simulation.

If data is of class sftime, then newdata MUST be of class stars or sftime, i.e. mixing form old-style classes (package spacetime) and new-style classes (sf, stars, sftime) is not supported.

Value

An object of the same class as newdata (deriving from ST). Attributes columns contain prediction and prediction variance.

Author(s)

Edzer Pebesma, Benedikt Graeler

References

Benedikt Graeler, Edzer Pebesma, Gerard Heuvelink. Spatio-Temporal Geostatistics using gstat. The R Journal 8(1), 204–218. https://journal.r-project.org/articles/RJ-2016-014/index.html

N.A.C. Cressie, 1993, Statistics for Spatial Data, Wiley.

Pebesma, E.J., 2004. Multivariable geostatistics in S: the gstat package. Computers and Geosciences, 30: 683-691.

See Also

krige0, gstat, predict, krigeTg

Examples

```
library(sp)
library(spacetime)
sumMetricVgm <- vgmST("sumMetric",
                      space = vgm( 4.4, "Lin", 196.6,  3),
                      time  = vgm( 2.2, "Lin",   1.1,  2),
                      joint = vgm(34.6, "Exp", 136.6, 12),
                      stAni = 51.7)

data(air)
suppressWarnings(proj4string(stations) <- CRS(proj4string(stations)))
rural = STFDF(stations, dates, data.frame(PM10 = as.vector(air)))

rr <- rural[,"2005-06-01/2005-06-03"]
rr <- as(rr,"STSDF")

x1 <- seq(from=6,to=15,by=1)
x2 <- seq(from=48,to=55,by=1)

DE_gridded <- SpatialPoints(cbind(rep(x1,length(x2)), rep(x2,each=length(x1))),
                            proj4string=CRS(proj4string(rr@sp)))
gridded(DE_gridded) <- TRUE
DE_pred <- STF(sp=as(DE_gridded,"SpatialPoints"), time=rr@time)
DE_kriged <- krigeST(PM10~1, data=rr, newdata=DE_pred,
                     modelList=sumMetricVgm)
gridded(DE_kriged@sp) <- TRUE
stplot(DE_kriged)
```

krigeSTSimTB *conditional/unconditional spatio-temporal simulation*

Description

conditional/unconditional spatio-temporal simulation based on turning bands

Usage

```
krigeSTSimTB(formula, data, newdata, modelList, nsim, progress = TRUE,
             nLyrs = 500, tGrid = NULL, sGrid = NULL, ceExt = 2, nmax = Inf)
```

Arguments

formula	the formula of the kriging predictor
data	conditioning data
newdata	locations in space and time where the simulation is carried out
modelList	the spatio-temporal variogram (from vgmST) defining the spatio-temporal covariance structure of the simulated Gaussian random field
nsim	number of simulations
progress	boolean; whether the progress should be shown in progress bar
nLyrs	number of layers used in the turning bands approach (default = 500)
tGrid	optional explicit temporal griding that shall be used
sGrid	optional explicit spatial griding that shall be used
ceExt	expansion in the circulant embedding, defaults to 2
nmax	number of nearest neighbours that shall e used, defaults to 'Inf' meaning all available points are used

Value

a spatio-temporal data frame with nSim simulations

Author(s)

Benedikt Graeler

References

Turning bands

Lantuejoul, C. (2002) Geostatistical Simulation: Models and Algorithms. Springer.

Matheron, G. (1973). The intrinsic random functions and their applications. Adv. Appl. Probab., 5, 439-468.

Strokorb, K., Ballani, F., and Schlather, M. (2014) Tail correlation functions of max-stable processes: Construction principles, recovery and diversity of some mixing max-stable processes with identical TCF. Extremes, Submitted.

Turning layers

Schlather, M. (2011) Construction of covariance functions and unconditional simulation of random fields. In Porcu, E., Montero, J.M. and Schlather, M., Space-Time Processes and Challenges Related to Environmental Problems. New York: Springer.

See Also

krigeSimCE

Examples

```
# see demo('circEmbeddingMeuse')
```

---

krigeTg *TransGaussian kriging using Box-Cox transforms*

Description

TransGaussian (ordinary) kriging function using Box-Cox transforms

Usage

```
krigeTg(formula, locations, newdata, model = NULL, ...,
 nmax = Inf, nmin = 0, maxdist = Inf, block = numeric(0),
 nsim = 0, na.action = na.pass, debug.level = 1,
 lambda = 1.0)
```

Arguments

formula	formula that defines the dependent variable as a linear model of independent variables; suppose the dependent variable has name z, for ordinary and use a formula like z~1; the dependent variable should be NOT transformed.
locations	object of class Spatial, with observations
newdata	Spatial object with prediction/simulation locations; the coordinates should have names as defined in locations
model	variogram model of the TRANSFORMED dependent variable, see vgm, or fit.variogram
nmax	for local kriging: the number of nearest observations that should be used for a kriging prediction or simulation, where nearest is defined in terms of the space of the spatial locations. By default, all observations are used
nmin	for local kriging: if the number of nearest observations within distance maxdist is less than nmin, a missing value will be generated; see maxdist

maxdist	for local kriging: only observations within a distance of maxdist from the prediction location are used for prediction or simulation; if combined with nmax, both criteria apply
block	does not function correctly, afaik
nsim	does not function correctly, afaik
na.action	function determining what should be done with missing values in 'newdata'. The default is to predict 'NA'. Missing values in coordinates and predictors are both dealt with.
lambda	value for the Box-Cox transform
debug.level	debug level, passed to predict; use -1 to see progress in percentage, and 0 to suppress all printed information
...	other arguments that will be passed to gstat

Details

Function krigeTg uses transGaussian kriging as explained in https://www.math.umd.edu/~bnk/bak/Splus/kriging.html.

As it uses the R/gstat krige function to derive everything, it needs in addition to ordinary kriging on the transformed scale a simple kriging step to find m from the difference between the OK and SK prediction variance, and a kriging/BLUE estimation step to obtain the estimate of μ.

For further details, see krige and predict.

Value

an SpatialPointsDataFrame object containing the fields: m for the m (Lagrange) parameter for each location; var1SK.pred the $c_0 C^{-1}$ correction obtained by muhat for the mean estimate at each location; var1SK.var the simple kriging variance; var1.pred the OK prediction on the transformed scale; var1.var the OK kriging variance on the transformed scale; var1TG.pred the transGaussian kriging predictor; var1TG.var the transGaussian kriging variance, obtained by $\phi'(\hat{\mu}, \lambda)^2 \sigma^2_{OK}$

Author(s)

Edzer Pebesma

References

N.A.C. Cressie, 1993, Statistics for Spatial Data, Wiley.

See Also

gstat, predict

Examples

```
library(sp)
data(meuse)
coordinates(meuse) = ~x+y
data(meuse.grid)
gridded(meuse.grid) = ~x+y
v = vgm(1, "Exp", 300)
x1 = krigeTg(zinc~1,meuse,meuse.grid,v, lambda=1) # no transform
x2 = krige(zinc~1,meuse,meuse.grid,v)
summary(x2$var1.var-x1$var1TG.var)
summary(x2$var1.pred-x1$var1TG.pred)
lambda = -0.25
m = fit.variogram(variogram((zinc^lambda-1)/lambda ~ 1,meuse), vgm(1, "Exp", 300))
x = krigeTg(zinc~1,meuse,meuse.grid,m,lambda=-.25)
spplot(x["var1TG.pred"], col.regions=bpy.colors())
summary(meuse$zinc)
summary(x$var1TG.pred)
```

---

map.to.lev *rearrange data frame for plotting with levelplot*

Description

rearrange data frame for plotting with levelplot

Usage

```
map.to.lev(data, xcol = 1, ycol = 2, zcol = c(3, 4), ns = names(data)[zcol])
```

Arguments

data	data frame, e.g. output from krige or predict
xcol	x-coordinate column number
ycol	y-coordinate column number
zcol	z-coordinate column number range
ns	names of the set of z-columns to be viewed

Value

data frame with the following elements:

x	x-coordinate for each row
y	y-coordinate for each row
z	column vector with each of the elements in columns zcol of data stacked
name	factor; name of each of the stacked z columns

See Also

image.data.frame, krige; for examples see predict; `levelplot` in package lattice.

`meuse.all` *Meuse river data set – original, full data set*

Description

This data set gives locations and top soil heavy metal concentrations (ppm), along with a number of soil and landscape variables, collected in a flood plain of the river Meuse, near the village Stein. Heavy metal concentrations are bulk sampled from an area of approximately 15 m x 15 m.

Usage

```
data(meuse.all)
```

Format

This data frame contains the following columns:

sample sample number

x a numeric vector; x-coordinate (m) in RDM (Dutch topographical map coordinates)

y a numeric vector; y-coordinate (m) in RDM (Dutch topographical map coordinates)

cadmium topsoil cadmium concentration, ppm.; note that zero cadmium values in the original data set have been shifted to 0.2 (half the lowest non-zero value)

copper topsoil copper concentration, ppm.

lead topsoil lead concentration, ppm.

zinc topsoil zinc concentration, ppm.

elev relative elevation

om organic matter, as percentage

ffreq flooding frequency class

soil soil type

lime lime class

landuse landuse class

dist.m distance to river Meuse (metres), as obtained during the field survey

in.pit logical; indicates whether this is a sample taken in a pit

in.meuse155 logical; indicates whether the sample is part of the `meuse` (i.e., filtered) data set; in addition to the samples in a pit, an sample (139) with outlying zinc content was removed

in.BMcD logical; indicates whether the sample is used as part of the subset of 98 points in the various interpolation examples of Burrough and McDonnell

Note

`sample` refers to original sample number. Eight samples were left out because they were not indicative for the metal content of the soil. They were taken in an old pit. One sample contains an outlying zinc value, which was also discarded for the meuse (155) data set.

Author(s)

The actual field data were collected by Ruud van Rijn and Mathieu Rikken; data compiled for R by Edzer Pebesma

References

P.A. Burrough, R.A. McDonnell, 1998. Principles of Geographical Information Systems. Oxford University Press.

See Also

meuse.alt

Examples

```
data(meuse.all)
summary(meuse.all)
```

---

meuse.alt *Meuse river altitude data set*

Description

This data set gives a point set with altitudes, digitized from the 1:10,000 topographical map of the Netherlands.

Usage

```
data(meuse.alt)
```

Format

This data frame contains the following columns:

x a numeric vector; x-coordinate (m) in RDM (Dutch topographical map coordinates)

y a numeric vector; y-coordinate (m) in RDM (Dutch topographical map coordinates)

alt altitude in m. above NAP (Dutch zero for sea level)

See Also

meuse.all

Examples

```
data(meuse.alt)
library(lattice)
xyplot(y~x, meuse.alt, aspect = "iso")
```

---

ncp.grid *Grid for the NCP, the Dutch part of the North Sea*

Description

Gridded data for the NCP (Nederlands Continentaal Plat, the Dutch part of the North Sea), for a 5 km x 5 km grid; stored as data.frame.

Usage

```
data(ncp.grid)
```

Format

This data frame contains the following columns:

x x-coordinate, UTM zone 31

y y-coordinate, UTM zone 31

depth sea water depth, m.

coast distance to the coast of the Netherlands, in km.

area identifier for administrative sub-areas

Author(s)

Dutch National Institute for Coastal and Marine Management (RIKZ); data compiled for R by Edzer Pebesma

See Also

fulmar

Examples

```
data(ncp.grid)
summary(ncp.grid)
```

ossfim *Kriging standard errors as function of grid spacing and block size*

Description

Calculate, for a given variogram model, ordinary block kriging standard errors as a function of sampling spaces and block sizes

Usage

```
ossfim(spacings = 1:5, block.sizes = 1:5, model, nmax = 25, debug = 0)
```

Arguments

spacings	range of grid (data) spacings to be used
block.sizes	range of block sizes to be used
model	variogram model, output of vgm
nmax	set the kriging neighbourhood size
debug	debug level; set to 32 to see a lot of output

Value

data frame with columns spacing (the grid spacing), block.size (the block size), and kriging.se (block kriging standard error)

Note

The idea is old, simple, but still of value. If you want to map a variable with a given accuracy, you will have to sample it. Suppose the variogram of the variable is known. Given a regular sampling scheme, the kriging standard error decreases when either (i) the data spacing is smaller, or (ii) predictions are made for larger blocks. This function helps quantifying this relationship. Ossfim probably refers to "optimal sampling scheme for isarithmic mapping".

Author(s)

Edzer Pebesma

References

Burrough, P.A., R.A. McDonnell (1999) Principles of Geographical Information Systems. Oxford University Press (e.g., figure 10.11 on page 261)

Burgess, T.M., R. Webster, A.B. McBratney (1981) Optimal interpolation and isarithmic mapping of soil properties. IV Sampling strategy. The journal of soil science 32(4), 643-660.

McBratney, A.B., R. Webster (1981) The design of optimal sampling schemes for local estimation and mapping of regionalized variables: 2 program and examples. Computers and Geosciences 7: 335-365.

See Also

krige

Examples

```
## Not run:
x <- ossfim(1:15,1:15, model = vgm(1,"Exp",15))
library(lattice)
levelplot(kriging.se~spacing+block.size, x,
  main = "Ossfim results, variogram 1 Exp(15)")

## End(Not run)
# if you wonder about the decrease in the upper left corner of the graph,
# try the above with nmax set to 100, or perhaps 200.
```

---

oxford *Oxford soil samples*

Description

Data: 126 soil augerings on a 100 x 100m square grid, with 6 columns and 21 rows. Grid is oriented with long axis North-north-west to South-south-east Origin of grid is South-south-east point, 100m outside grid.

Original data are part of a soil survey carried out by P.A. Burrough in 1967. The survey area is located on the chalk downlands on the Berkshire Downs in Oxfordshire, UK. Three soil profile units were recognised on the shallow Rendzina soils; these are Ia - very shallow, grey calcareous soils less than 40cm deep over chalk; Ct - shallow to moderately deep, grey-brown calcareous soils on calcareous colluvium, and Cr: deep, moderately acid, red-brown clayey soils. These soil profile classes were registered at every augering.

In addition, an independent landscape soil map was made by interpolating soil boundaries between these soil types, using information from the changes in landform. Because the soil varies over short distances, this field mapping caused some soil borings to receive a different classification from the classification based on the point data.

Also registered at each auger point were the site elevation (m), the depth to solid chalk rock (in cm) and the depth to lime in cm. Also, the percent clay content, the Munsell colour components of VALUE and CHROMA , and the lime content of the soil (as tested using HCl) were recorded for the top two soil layers (0-20cm and 20-40cm).

Samples of topsoil taken as a bulk sample within a circle of radius 2.5m around each sample point were used for the laboratory determination of Mg (ppm), OM1 %, CEC as mequ/100g air dry soil, pH, P as ppm and K (ppm).

Usage

```
data(oxford)
```

Format

This data frame contains the following columns:

PROFILE profile number
XCOORD x-coordinate, field, non-projected
YCOORD y-coordinate, field, non-projected
ELEV elevation, m.
PROFCLASS soil class, obtained by classifying the soil profile at the sample site
MAPCLASS soil class, obtained by looking up the site location in the soil map
VAL1 Munsell colour component VALUE, 0-20 cm
CHR1 Munsell colour component CHROMA, 20-40 cm
LIME1 Lime content (tested using HCl), 0-20 cm
VAL2 Munsell colour component VALUE, 0-20 cm
CHR2 Munsell colour component CHROMA, 20-40 cm
LIME2 Lime content (tested using HCl), 20-40 cm
DEPTHCM soil depth, cm
DEP2LIME depth to lime, cm
PCLAY1 percentage clay, 0-20 cm
PCLAY2 percentage clay, 20-40 cm
MG1 Magnesium content (ppm), 0-20 cm
OM1 organic matter (%), 0-20 cm
CEC1 CES as mequ/100g air dry soil, 0-20 cm
PH1 pH, 0-20 cm
PHOS1 Phosphorous, 0-20 cm, ppm
POT1 K (potassium), 0-20 cm, ppm

Note

`oxford.jpg`, in the gstat package external directory (see example below), shows an image of the soil map for the region

Author(s)

P.A. Burrough; compiled for R by Edzer Pebesma

References

P.A. Burrough, R.A. McDonnell, 1998. Principles of Geographical Information Systems. Oxford University Press.

Examples

```
data(oxford)
summary(oxford)
# open the following file with a jpg viewer:
system.file("external/oxford.jpg", package="gstat")
```

pcb *PCB138 measurements in sediment at the NCP, the Dutch part of the North Sea*

Description

PCB138 measurements in sediment at the NCP, which is the Dutch part of the North Sea

Usage

```
data(pcb)
```

Format

This data frame contains the following columns:

year measurement year

x x-coordinate; UTM zone 31

y y-coordinate; UTM zone 31

coast distance to coast of the Netherlands, in km.

depth sea water depth, m.

PCB138 PCB-138, measured on the sediment fraction smaller than 63 μ, in $\mu g/kg$ dry matter; BUT SEE NOTE BELOW

yf year; as factor

Note

A note of caution: The PCB-138 data are provided only to be able to re-run the analysis done in Pebesma and Duin (2004; see references below). If you want to use these data for comparison with PCB measurements elsewhere, or if you want to compare them to regulation standards, or want to use these data for any other purpose, you should first contact mailto:basisinfodesk@rikz.rws.minvenw.nl. The reason for this is that several normalisations were carried out that are not reported here, nor in the paper below.

References

Pebesma, E. J., and Duin, R. N. M. (2005). Spatial patterns of temporal change in North Sea sediment quality on different spatial scales. In P. Renard, H. Demougeot-Renard and R. Froidevaux (Eds.), Geostatistics for Environmental Applications: Proceedings of the Fifth European Conference on Geostatistics for Environmental Applications (pp. 367-378): Springer.

See Also

ncp.grid

Examples

```
data(pcb)
library(lattice)
xyplot(y~x|as.factor(yf), pcb, aspect = "iso")
# demo(pcb)
```

`plot.gstatVariogram` *Plot a sample variogram, and possibly a fitted model*

Description

Creates a variogram plot

Usage

```
## S3 method for class 'gstatVariogram'
plot(x, model = NULL, ylim, xlim, xlab = "distance",
 ylab = attr(x, "what"), panel = vgm.panel.xyplot, multipanel = TRUE,
 plot.numbers = FALSE, scales, ids = x$id, group.id = TRUE, skip,
 layout, ...)
## S3 method for class 'variogramMap'
plot(x, np = FALSE, skip, threshold, ...)
## S3 method for class 'StVariogram'
plot(x, model = NULL, ..., col = bpy.colors(), xlab, ylab,
 map = TRUE, convertMonths = FALSE, as.table = TRUE, wireframe = FALSE,
 diff = FALSE, all = FALSE)
```

Arguments

`x`	object obtained from the method variogram, possibly containing directional or cross variograms, space-time variograms and variogram model information
`model`	in case of a single variogram: a variogram model, as obtained from vgm or fit.variogram, to be drawn as a line in the variogram plot; in case of a set of variograms and cross variograms: a list with variogram models; in the spatio-temporal case, a single or a list of spatio-temporal models that will be plotted next to each other for visual comparison.
`ylim`	numeric; vector of length 2, limits of the y-axis
`xlim`	numeric; vector of length 2, limits of the x-axis
`xlab`	character; x-axis label
`ylab`	character; y-axis label
`panel`	panel function
`multipanel`	logical; if TRUE, directional variograms are plotted in different panels, if FALSE, directional variograms are plotted in the same graph, using color, colored lines and symbols to distinguish them

plot.numbers	logical or numeric; if TRUE, plot number of point pairs next to each plotted semivariance symbol, if FALSE these are omitted. If numeric, TRUE is assumed and the value is passed as the relative distance to be used between symbols and numeric text values (default 0.03).
scales	optional argument that will be passed to xyplot in case of the plotting of variograms and cross variograms; use the value list(relation = "same") if y-axes need to share scales
ids	ids of the data variables and variable pairs
group.id	logical; control for directional multivariate variograms: if TRUE, panels divide direction and colors indicate variables (ids), if FALSE panels divide variables/variable pairs and colors indicate direction
skip	logical; can be used to arrange panels, see xyplot
layout	integer vector; can be used to set panel layout: c(ncol,nrow)
np	logical (only for plotting variogram maps); if TRUE, plot number of point pairs, if FALSE plot semivariances
threshold	semivariogram map values based on fewer point pairs than threshold will not be plotted
...	any arguments that will be passed to the panel plotting functions (such as auto.key in examples below)
col	colors to use
map	logical; if TRUE, plot space-time variogram map
convertMonths	logical; if TRUE, yearmon time lags will be unit converted and plotted as (integer) months, and no longer match the numeric representation of yearmon, which has years as unit
as.table	controls the plotting order for multiple panels, see xyplot for details.
wireframe	logical; if TRUE, produce a wireframe plot
diff	logical; if TRUE, plot difference between model and sample variogram; ignores all.
all	logical; if TRUE, plot sample and model variogram(s) in single wireframes.

Details

Please note that in the spatio-temporal case the levelplot and wireframe plots use the spatial distances averaged for each time lag avgDist. For strongly varying spatial locations over time, please check the distance columns dist and avgDist of the spatio-temporal sample variogram. The lattice::cloud function is one option to plot irregular 3D data.

Value

returns (or plots) the variogram plot

Note

currently, plotting models and/or point pair numbers is not supported when a variogram is both directional and multivariable; also, three-dimensional directional variograms will probably not be displayed correctly.

Author(s)

Edzer Pebesma

See Also

variogram, fit.variogram, vgm variogramLine,

Examples

```
library(sp)
data(meuse)
coordinates(meuse) = ~x+y
vgm1 <- variogram(log(zinc)~1, meuse)
plot(vgm1)
model.1 <- fit.variogram(vgm1,vgm(1,"Sph",300,1))
plot(vgm1, model=model.1)
plot(vgm1, plot.numbers = TRUE, pch = "+")
vgm2 <- variogram(log(zinc)~1, meuse, alpha=c(0,45,90,135))
plot(vgm2)
# the following demonstrates plotting of directional models:
model.2 <- vgm(.59,"Sph",926,.06,anis=c(0,0.3))
plot(vgm2, model=model.2)

g = gstat(NULL, "zinc < 200", I(zinc<200)~1, meuse)
g = gstat(g, "zinc < 400", I(zinc<400)~1, meuse)
g = gstat(g, "zinc < 800", I(zinc<800)~1, meuse)
# calculate multivariable, directional variogram:
v = variogram(g, alpha=c(0,45,90,135))
plot(v, group.id = FALSE, auto.key = TRUE) # id and id pairs panels
plot(v, group.id = TRUE, auto.key = TRUE)  # direction panels

# variogram maps:
plot(variogram(g, cutoff=1000, width=100, map=TRUE),
    main = "(cross) semivariance maps")
plot(variogram(g, cutoff=1000, width=100, map=TRUE), np=TRUE,
    main = "number of point pairs")
```

---

plot.pointPairs *Plot a point pairs, identified from a variogram cloud*

Description

Plot a point pairs, identified from a variogram cloud

Usage

```
## S3 method for class 'pointPairs'
plot(x, data, xcol = data$x, ycol = data$y, xlab = "x coordinate",
ylab = "y coordinate", col.line = 2, line.pch = 0, main = "selected point pairs", ...)
```

Arguments

x	object of class "pointPairs", obtained from the function plot.variogramCloud, containing point pair indices
data	data frame to which the indices refer (from which the variogram cloud was calculated)
xcol	numeric vector with x-coordinates of data
ycol	numeric vector with y-coordinates of data
xlab	x-axis label
ylab	y-axis label
col.line	color for lines connecting points
line.pch	if non-zero, symbols are also plotted at the middle of line segments, to mark lines too short to be visible on the plot; the color used is col.line; the value passed to this argument will be used as plotting symbol (pch)
main	title of plot
...	arguments, further passed to xyplot

Value

plots the data locations, with lines connecting the point pairs identified (and refered to by indices in) x

Author(s)

Edzer Pebesma

See Also

plot.variogramCloud

Examples

```
### The following requires interaction, and is therefore outcommented
#data(meuse)
#coordinates(meuse) = ~x+y
#vgm1 <- variogram(log(zinc)~1, meuse, cloud = TRUE)
#pp <- plot(vgm1, id = TRUE)
### Identify the point pairs
#plot(pp, data = meuse) # meuse has x and y as coordinates
```

plot.variogramCloud *Plot and Identify Data Pairs on Sample Variogram Cloud*

Description

Plot a sample variogram cloud, possibly with identification of individual point pairs

Usage

```
## S3 method for class 'variogramCloud'
plot(x, identify = FALSE, digitize = FALSE, xlim, ylim, xlab, ylab,
 keep = FALSE, ...)
```

Arguments

x	object of class variogramCloud
identify	logical; if TRUE, the plot allows identification of a series of individual point pairs that correspond to individual variogram cloud points (use left mouse button to select; right mouse button ends)
digitize	logical; if TRUE, select point pairs by digitizing a region with the mouse (left mouse button adds a point, right mouse button ends)
xlim	limits of x-axis
ylim	limits of y-axis
xlab	x axis label
ylab	y axis label
keep	logical; if TRUE and identify is TRUE, the labels identified and their position are kept and glued to object x, which is returned. Subsequent calls to plot this object will now have the labels shown, e.g. to plot to hardcopy
...	parameters that are passed through to plot.gstatVariogram (in case of identify = FALSE) or to plot (in case of identify = TRUE)

Value

If identify or digitize is TRUE, a data frame of class pointPairs with in its rows the point pairs identified (pairs of row numbers in the original data set); if identify is F, a plot of the variogram cloud, which uses plot.gstatVariogram

If in addition to identify, keep is also TRUE, an object of class variogramCloud is returned, having attached to it attributes "sel" and "text", which will be used in subsequent calls to plot.variogramCloud with identify set to FALSE, to plot the text previously identified.

If in addition to digitize, keep is also TRUE, an object of class variogramCloud is returned, having attached to it attribute "poly", which will be used in subsequent calls to plot.variogramCloud with digitize set to FALSE, to plot the digitized line.

In both of the keep = TRUE cases, the attribute ppairs of class pointPairs is present, containing the point pairs identified.

Author(s)

Edzer Pebesma

See Also

variogram, plot.gstatVariogram, plot.pointPairs, identify, locator

Examples

```
library(sp)
data(meuse)
coordinates(meuse) = ~x+y
plot(variogram(log(zinc)~1, meuse, cloud=TRUE))
## commands that require interaction:
# x <- variogram(log(zinc)~1, loc=~x+y, data=meuse, cloud=TRUE)
# plot(plot(x, identify = TRUE), meuse)
# plot(plot(x, digitize = TRUE), meuse)
```

---

predict *Multivariable Geostatistical Prediction and Simulation*

Description

The function provides the following prediction methods: simple, ordinary, and universal kriging, simple, ordinary, and universal cokriging, point- or block-kriging, and conditional simulation equivalents for each of the kriging methods.

Usage

```
## S3 method for class 'gstat'
predict(object, newdata, block = numeric(0), nsim = 0,
 indicators = FALSE, BLUE = FALSE, debug.level = 1, mask,
 na.action = na.pass, sps.args = list(n = 500, type = "regular",
 offset = c(.5, .5)), ...)
```

Arguments

object	object of class gstat, see gstat and krige
newdata	data frame with prediction/simulation locations; should contain columns with the independent variables (if present) and the coordinates with names as defined in locations; or: polygons, see below
block	block size; a vector with 1, 2 or 3 values containing the size of a rectangular in x-, y- and z-dimension respectively (0 if not set), or a data frame with 1, 2 or 3 columns, containing the points that discretize the block in the x-, y- and z-dimension to define irregular blocks relative to (0,0) or (0,0,0)—see also the details section below. By default, predictions or simulations refer to the support of the data values.

nsim	integer; if set to a non-zero value, conditional simulation is used instead of kriging interpolation. For this, sequential Gaussian or indicator simulation is used (depending on the value of indicators), following a single random path through the data.
indicators	logical; only relevant if nsim is non-zero; if TRUE, use indicator simulation, else use Gaussian simulation
BLUE	logical; if TRUE return the BLUE trend estimates only, if FALSE return the BLUP predictions (kriging)
debug.level	integer; set gstat internal debug level, see below for useful values. If set to -1 (or any negative value), a progress counter is printed
mask	not supported anymore – use na.action; logical or numerical vector; pattern with valid values in newdata (marked as TRUE, non-zero, or non-NA); if mask is specified, the returned data frame will have the same number and order of rows in newdata, and masked rows will be filled with NA's.
na.action	function determining what should be done with missing values in 'newdata'. The default is to predict 'NA'. Missing values in coordinates and predictors are both dealt with.
sps.args	when newdata is of class SpatialPolygons or SpatialPolygonsDataFrame this argument list gets passed to spsample to control the discretizing of polygons
...	ignored (but necessary for the S3 generic/method consistency)

Details

When a non-stationary (i.e., non-constant) mean is used, both for simulation and prediction purposes the variogram model defined should be that of the residual process, not that of the raw observations.

For irregular block kriging, coordinates should discretize the area relative to (0), (0,0) or (0,0,0); the coordinates in newdata should give the centroids around which the block should be located. So, suppose the block is discretized by points (3,3) (3,5) (5,5) and (5,3), we should pass point (4,4) in newdata and pass points (-1,-1) (-1,1) (1,1) (1,-1) to the block argument. Although passing the uncentered block and (0,0) as newdata may work for global neighbourhoods, neighbourhood selection is always done relative to the centroid values in newdata.

If newdata is of class SpatialPolygons or SpatialPolygonsDataFrame, then the block average for each of the polygons or polygon sets is calculated, using spsample to discretize the polygon(s). Argument sps.args controls the parameters used for spsample. The "location" with respect to which neighbourhood selection is done is for each polygon the SpatialPolygons polygon label point; if you use local neighbourhoods you should check out where these points are—it may be well outside the polygon itself.

The algorithm used by gstat for simulation random fields is the sequential simulation algorithm. This algorithm scales well to large or very large fields (e.g., more than 10^6 nodes). Its power lies in using only data and simulated values in a local neighbourhood to approximate the conditional distribution at that location, see nmax in krige and gstat. The larger nmax, the better the approximation, the smaller nmax, the faster the simulation process. For selecting the nearest nmax data or previously simulated points, gstat uses a bucket PR quadtree neighbourhood search algorithm; see the reference below.

For sequential Gaussian or indicator simulations, a random path through the simulation locations is taken, which is usually done for sequential simulations. The reason for this is that the local approximation of the conditional distribution, using only the `nmax` neareast observed (or simulated) values may cause spurious correlations when a regular path would be followed. Following a single path through the locations, gstat reuses the expensive results (neighbourhood selection and solution to the kriging equations) for each of the subsequent simulations when multiple realisations are requested. You may expect a considerable speed gain in simulating 1000 fields in a single call to predict, compared to 1000 calls, each for simulating a single field.

The random number generator used for generating simulations is the native random number generator of the environment (R, S); fixing randomness by setting the random number seed with `set.seed()` works.

When mean coefficient are not supplied, they are generated as well from their conditional distribution (assuming multivariate normal, using the generalized least squares BLUE estimate and its estimation covariance); for a reference to the algorithm used see Abrahamsen and Benth, Math. Geol. 33(6), page 742 and leave out all constraints.

Memory requirements for sequential simulation: let n be the product of the number of variables, the number of simulation locations, and the number of simulations required in a single call. the gstat C function `gstat_predict` requires a table of size n * 12 bytes to pass the simulations back to R, before it can free n * 4 bytes. Hopefully, R does not have to duplicate the remaining n * 8 bytes when the coordinates are added as columns, and when the resulting matrix is coerced to a `data.frame`.

Useful values for `debug.level`: 0: suppres any output except warning and error messages; 1: normal output (default): short data report, program action and mode, program progress in %, total execution time; 2: print the value of all global variables, all files read and written, and include source file name and line number in error messages; 4: print OLS and WLS fit diagnostics; 8: print all data after reading them; 16: print the neighbourhood selection for each prediction location; 32: print (generalised) covariance matrices, design matrices, solutions, kriging weights, etc.; 64: print variogram fit diagnostics (number of iterations and variogram model in each iteration step) and order relation violations (indicator kriging values before and after order relation correction); 512: print block (or area) discretization data for each prediction location. To combine settings, sum their respective values. Negative values for `debug.level` are equal to positive, but cause the progress counter to work.

For data with longitude/latitude coordinates (checked by `is.projected`), gstat uses great circle distances in km to compute spatial distances. The user should make sure that the semivariogram model used is positive definite on a sphere.

Value

a data frame containing the coordinates of `newdata`, and columns of prediction and prediction variance (in case of kriging) or the columns of the conditional Gaussian or indicator simulations

Author(s)

Edzer Pebesma

References

N.A.C. Cressie, 1993, Statistics for Spatial Data, Wiley.

Pebesma, E.J., 2004. Multivariable geostatistics in S: the gstat package. Computers and Geosciences, 30: 683-691.

See Also

gstat, krige

Examples

```
# generate 5 conditional simulations
library(sp)
data(meuse)
coordinates(meuse) = ~x+y
v <- variogram(log(zinc)~1, meuse)
m <- fit.variogram(v, vgm(1, "Sph", 300, 1))
plot(v, model = m)
set.seed(131)
data(meuse.grid)
gridded(meuse.grid) = ~x+y
sim <- krige(formula = log(zinc)~1, meuse, meuse.grid, model = m,
 nmax = 10, beta = 5.9, nsim = 5) # for speed -- 10 is too small!!
# show all 5 simulation
spplot(sim)

# calculate generalised least squares residuals w.r.t. constant trend:
g <- gstat(NULL, "log.zinc", log(zinc)~1, meuse, model = m)
blue0 <- predict(g, newdata = meuse, BLUE = TRUE)
blue0$blue.res <- log(meuse$zinc) - blue0$log.zinc.pred
bubble(blue0, zcol = "blue.res", main = "GLS residuals w.r.t. constant")

# calculate generalised least squares residuals w.r.t. linear trend:
m <- fit.variogram(variogram(log(zinc)~sqrt(dist.m), meuse),
 vgm(1, "Sph", 300, 1))
g <- gstat(NULL, "log.zinc", log(zinc)~sqrt(dist.m), meuse, model = m)
blue1 <- predict(g, meuse, BLUE = TRUE)
blue1$blue.res <- log(meuse$zinc) - blue1$log.zinc.pred
bubble(blue1, zcol = "blue.res",
 main = "GLS residuals w.r.t. linear trend")

# unconditional simulation on a 100 x 100 grid
xy <- expand.grid(1:100, 1:100)
names(xy) <- c("x","y")
gridded(xy) = ~x+y
g.dummy <- gstat(formula = z~1, dummy = TRUE, beta = 0,
 model = vgm(1,"Exp",15), nmax = 10) # for speed -- 10 is too small!!
yy <- predict(g.dummy, xy, nsim = 4)
# show one realisation:
spplot(yy[1])
# show all four:
spplot(yy)
```

progress *Get or set progress indicator*

Description

Get or set progress indicator

Usage

```
get_gstat_progress()
set_gstat_progress(value)
```

Arguments

value	logical

Value

return the logical value indicating whether progress bars should be given

Author(s)

Edzer Pebesma

Examples

```
set_gstat_progress(FALSE)
get_gstat_progress()
```

show.vgms *Plot Variogram Model Functions*

Description

Creates a trellis plot for a range of variogram models, possibly with nugget; and optionally a set of Matern models with varying smoothness.

Usage

```
show.vgms(min = 1e-12 * max, max = 3, n = 50, sill = 1, range = 1,
    models = as.character(vgm()$short[c(1:17)]), nugget = 0, kappa.range = 0.5,
 plot = TRUE, ..., as.groups = FALSE)
```

Arguments

min	numeric; start distance value for semivariance calculation beyond the first point at exactly zero
max	numeric; maximum distance for semivariance calculation and plotting
n	integer; number of points to calculate distance values
sill	numeric; (partial) sill(s) of the variogram model
range	numeric; range(s) of the variogram model
models	character; variogram model(s) to be plotted
nugget	numeric; nugget component(s) for variogram models
kappa.range	numeric; if this is a vector with more than one element, only a range of Matern models is plotted with these kappa values
plot	logical; if TRUE, a plot is returned with the models specified; if FALSE, the data prepared for this plot is returned
...	passed on to the call to xyplot
as.groups	logical; if TRUE, different models are plotted with different lines in a single panel, else, in one panel per model

Value

returns a (Trellis) plot of the variogram models requested; see examples. I do currently have strong doubts about the "correctness" of the "Hol" model. The "Spl" model does seem to need a very large range value (larger than the study area?) to be of some value.

If plot is FALSE, a data frame with the data prepared to plot is being returned.

Note

the min argument is supplied because the variogram function may be discontinuous at distance zero, surely when a positive nugget is present.

Author(s)

Edzer Pebesma

See Also

vgm, variogramLine,

Examples

```
show.vgms()
show.vgms(models = c("Exp", "Mat", "Gau"), nugget = 0.1)
# show a set of Matern models with different smoothness:
show.vgms(kappa.range = c(.1, .2, .5, 1, 2, 5, 10), max = 10)
# show a set of Exponential class models with different shape parameter:
show.vgms(kappa.range = c(.05, .1, .2, .5, 1, 1.5, 1.8, 1.9, 2), models = "Exc", max = 10)
# show a set of models with different shape parameter of M. Stein's representation of the Matern:
show.vgms(kappa.range = c(.01, .02, .05, .1, .2, .5, 1, 2, 5, 1000), models = "Ste", max = 2)
```

`sic2004` *Spatial Interpolation Comparison 2004 data set: Natural Ambient Radioactivity*

Description

The text below was copied from the original sic2004 event, which is no longer online available.

The variable used in the SIC 2004 exercise is natural ambient radioactivity measured in Germany. The data, provided kindly by the German Federal Office for Radiation Protection (BfS), are gamma dose rates reported by means of the national automatic monitoring network (IMIS).

In the frame of SIC2004, a rectangular area was used to select 1008 monitoring stations (from a total of around 2000 stations). For these 1008 stations, 11 days of measurements have been randomly selected during the last 12 months and the average daily dose rates calculated for each day. Hence, we ended up having 11 data sets.

Prior information (sic.train): 10 data sets of 200 points that are identical for what concerns the locations of the monitoring stations have been prepared. These locations have been randomly selected (see Figure 1). These data sets differ only by their Z values since each set corresponds to 1 day of measurement made during the last 14 months. No information will be provided on the date of measurement. These 10 data sets (10 days of measurements) can be used as prior information to tune the parameters of the mapping algorithms. No other information will be provided about these sets. Participants are free of course to gather more information about the variable in the literature and so on.

The 200 monitoring stations above were randomly taken from a larger set of 1008 stations. The remaining 808 monitoring stations have a topology given in sic.pred. Participants to SIC2004 will have to estimate the values of the variable taken at these 808 locations.

The SIC2004 data (sic.val, variable dayx): The exercise consists in using 200 measurements made on a 11th day (THE data of the exercise) to estimate the values observed at the remaining 808 locations (hence the question marks as symbols in the maps shown in Figure 3). These measurements will be provided only during two weeks (15th of September until 1st of October 2004) on a web page restricted to the participants. The true values observed at these 808 locations will be released only at the end of the exercise to allow participants to write their manuscripts (sic.test, variables dayx and joker).

In addition, a joker data set was released (sic.val, variable joker), which contains an anomaly. The anomaly was generated by a simulation model, and does not represent measured levels.

Usage

```
data(sic2004) #
```

Format

The data frames contain the following columns:

record this integer value is the number (unique value) of the monitoring station chosen by us.

x X-coordinate of the monitoring station indicated in meters

y Y-coordinate of the monitoring station indicated in meters

day01 mean gamma dose rate measured during 24 hours, at day01. Units are nanoSieverts/hour

day02 same, for day 02

day03 ...

day04 ...

day05 ...

day06 ...

day07 ...

day08 ...

day09 ...

day10 ...

dayx the data observed at the 11-th day

joker the joker data set, containing an anomaly not present in the training data

Note

the data set sic.grid provides a set of points on a regular grid (almost 10000 points) covering the area; this is convenient for interpolation; see the function `makegrid` in package sp.

The coordinates have been projected around a point located in the South West of Germany. Hence, a few coordinates have negative values as can be guessed from the Figures below.

Author(s)

Data: the German Federal Office for Radiation Protection (BfS), https://www.bfs.de/EN/home/home_node.html, data provided by Gregoire Dubois, R compilation by Edzer Pebesma.

Examples

```
data(sic2004)
# FIGURE 1. Locations of the 200 monitoring stations for the 11 data sets.
# The values taken by the variable are known.
plot(y~x,sic.train,pch=1,col="red", asp=1)

# FIGURE 2. Locations of the 808 remaining monitoring stations at which
# the values of the variable must be estimated.
plot(y~x,sic.pred,pch="?", asp=1, cex=.8) # Figure 2

# FIGURE 3. Locations of the 1008 monitoring stations (exhaustive data sets).
# Red circles are used to estimate values located at the questions marks
plot(y~x,sic.train,pch=1,col="red", asp=1)
points(y~x, sic.pred, pch="?", cex=.8)
```

sic97 *Spatial Interpolation Comparison 1997 data set: Swiss Rainfall*

Description

The text below is copied from the data item at ai-geostats, (link no longer working).

Usage

```
data(sic97) #
```

Format

The data frames contain the following columns:

ID this integer value is the number (unique value) of the monitoring station

rainfall rainfall amount, in 10th of mm

Note

See the pdf that accompanies the original file for a description of the data. The .dxf file with the Swiss border is not included here.

Author(s)

Gregoire Dubois and others.

Examples

```
data(sic97)
image(demstd)
points(sic_full, pch=1)
points(sic_obs, pch=3)
```

spplot.vcov *Plot map matrix of prediction error variances and covariances*

Description

Plot map matrix of prediction error variances and covariances

Usage

```
spplot.vcov(x, ...)
```

Arguments

x	Object of class SpatialPixelsDataFrame or SpatialGridDataFrame, resulting from a krige call with multiple variables (cokriging
...	remaining arguments passed to spplot

Value

The plotted object, of class trellis; see `spplot` in package **sp**.

Author(s)

Edzer Pebesma

---

tull *Südliche Tullnerfeld data set*

Description

The Südliche Tullnerfeld is a part of the Danube river basin in central Lower Austria and due to its homogeneous aquifer well suited for a model-oriented geostatistical analysis. It contains 36 official water quality measurement stations, which are irregularly spread over the region.

Usage

```
data(tull)
```

Format

The data frames contain the following columns:

x X location in meter

y Y location in meter

S411 Station name

S429 Station name

S849 Station name

S854 Station name

S1502 Station name

S1584 Station name

S1591 Station name

S2046 Station name

S2047 Station name

S2048 Station name

S2049 Station name

S2051 Station name

S2052 Station name

S2053 Station name

S2054 Station name

S2055 Station name

S2057 Station name

S2058 Station name

S2059 Station name

S2060 Station name

S2061 Station name

S2062 Station name

S2063 Station name

S2064 Station name

S2065 Station name

S2066 Station name

S2067 Station name

S2070 Station name

S2071 Station name

S2072 Station name

S2128 Station name

S5319 Station name

S5320 Station name

S5321 Station name

S5322 Station name

S5323 Station name

References

Werner G. Müller, Collecting Spatial Data, 3rd edition. Springer Verlag, Heidelberg, 2007

Examples

```
data(tull)

# TULLNREG = read.csv("TULLNREG.csv")

# I modified tulln36des.csv, such that the first line only contained: x,y
# resulting in row.names that reflect the station ID, as in
# tull36 = read.csv("tulln36des.csv")

# Chlorid92 was read & converted by:
#Chlorid92=read.csv("Chlorid92.csv")
```

```
#Chlorid92$Datum = as.POSIXct(strptime(Chlorid92$Datum, "%d.%m.%y"))

summary(tull36)
summary(TULLNREG)
summary(Chlorid92)

# stack & join data to x,y,Date,Chloride form:
cl.st = stack(Chlorid92[-1])
names(cl.st) = c("Chloride", "Station")
cl.st$Date = rep(Chlorid92$Datum, length(names(Chlorid92))-1)
cl.st$x = tull36[match(cl.st[,"Station"], row.names(tull36)), "x"]
cl.st$y = tull36[match(cl.st[,"Station"], row.names(tull36)), "y"]
# library(lattice)
# xyplot(Chloride~Date|Station, cl.st)
# xyplot(y~x|Date, cl.st, asp="iso", layout=c(16,11))
summary(cl.st)
plot(TULLNREG, pch=3, asp=1)
points(y~x, cl.st, pch=16)
```

---

variogram *Calculate Sample or Residual Variogram or Variogram Cloud*

Description

Calculates the sample variogram from data, or in case of a linear model is given, for the residuals, with options for directional, robust, and pooled variogram, and for irregular distance intervals.

In case spatio-temporal data is provided, the function variogramST is called with a different set of parameters.

Usage

```
## S3 method for class 'gstat'
variogram(object, ...)
## S3 method for class 'formula'
variogram(object, locations = coordinates(data), data, ...)
## Default S3 method:
variogram(object, locations, X, cutoff, width = cutoff/15,
 alpha = 0, beta = 0, tol.hor = 90/length(alpha), tol.ver =
 90/length(beta), cressie = FALSE, dX = numeric(0), boundaries =
 numeric(0), cloud = FALSE, trend.beta = NULL, debug.level = 1,
 cross = TRUE, grid, map = FALSE, g = NULL, ..., projected = TRUE,
 lambda = 1.0, verbose = FALSE, covariogram = FALSE, PR = FALSE,
 pseudo = -1)
## S3 method for class 'gstatVariogram'
print(x, ...)
## S3 method for class 'variogramCloud'
print(x, ...)
```

Arguments

object	object of class gstat; in this form, direct and cross (residual) variograms are calculated for all variables and variable pairs defined in object; in case of variogram.formula, formula defining the response vector and (possible) regressors, in case of absence of regressors, use e.g. z~1; in case of variogram.default: list with for each variable the vector with responses (should not be called directly)
data	data frame where the names in formula are to be found
locations	spatial data locations. For variogram.formula: a formula with only the coordinate variables in the right hand (explanatory variable) side e.g. ~x+y; see examples. For variogram.default: list with coordinate matrices, each with the number of rows matching that of corresponding vectors in y; the number of columns should match the number of spatial dimensions spanned by the data (1 (x), 2 (x,y) or 3 (x,y,z)).
...	any other arguments that will be passed to variogram.default (ignored)
X	(optional) list with for each variable the matrix with regressors/covariates; the number of rows should match that of the correspoding element in y, the number of columns equals the number of regressors (including intercept)
cutoff	spatial separation distance up to which point pairs are included in semivariance estimates; as a default, the length of the diagonal of the box spanning the data is divided by three.
width	the width of subsequent distance intervals into which data point pairs are grouped for semivariance estimates
alpha	direction in plane (x,y), in positive degrees clockwise from positive y (North): alpha=0 for direction North (increasing y), alpha=90 for direction East (increasing x); optional a vector of directions in (x,y)
beta	direction in z, in positive degrees up from the (x,y) plane;
optional a vector of directions	
tol.hor	horizontal tolerance angle in degrees
tol.ver	vertical tolerance angle in degrees
cressie	logical; if TRUE, use Cressie"s robust variogram estimate; if FALSE use the classical method of moments variogram estimate
dX	include a pair of data points $y(s_1),y(s_2)$ taken at locations s_1 and s_2 for sample variogram calculation only when $\|\|x(s_1)-x(s_2)\|\| < dX$ with and $x(s_i)$ the vector with regressors at location s_i, and $\|\|.\|\|$ the 2-norm. This allows pooled estimation of within-strata variograms (use a factor variable as regressor, and dX=0.5), or variograms of (near-)replicates in a linear model (addressing point pairs having similar values for regressors variables)
boundaries	numerical vector with distance interval upper boundaries; values should be strictly increasing
cloud	logical; if TRUE, calculate the semivariogram cloud

trend.beta	vector with trend coefficients, in case they are known. By default, trend coefficients are estimated from the data.
debug.level	integer; set gstat internal debug level
cross	logical or character; if FALSE, no cross variograms are computed when object is of class gstat and has more than one variable; if TRUE, all direct and cross variograms are computed; if equal to "ST", direct and cross variograms are computed for all pairs involving the first (non-time lagged) variable; if equal to "ONLY", only cross variograms are computed (no direct variograms).
formula	formula, specifying the dependent variable and possible covariates
x	object of class variogram or variogramCloud to be printed
grid	grid parameters, if data are gridded (not to be called directly; this is filled automatically)
map	logical; if TRUE, and cutoff and width are given, a variogram map is returned. This requires package sp. Alternatively, a map can be passed, of class SpatialDataFrameGrid (see sp docs)
g	NULL or object of class gstat; may be used to pass settable parameters and/or variograms; see example
projected	logical; if FALSE, data are assumed to be unprojected, meaning decimal longitude/latitude. For projected data, Euclidian distances are computed, for unprojected great circle distances (km). In variogram.formula or variogram.gstat, for data deriving from class Spatial, projection is detected automatically using is.projected
lambda	test feature; not working (yet)
verbose	logical; print some progress indication
pseudo	integer; use pseudo cross variogram for computing time-lagged spatial variograms? -1: find out from coordinates – if they are equal then yes, else no; 0: no; 1: yes.
covariogram	logical; compute covariogram instead of variogram?
PR	logical; compute pairwise relative variogram (does NOT check whether variable is strictly positive)

Value

If map is TRUE (or a map is passed), a grid map is returned containing the (cross) variogram map(s). See package sp.

In other cases, an object of class "gstatVariogram" with the following fields:

np	the number of point pairs for this estimate; in case of a variogramCloud see below
dist	the average distance of all point pairs considered for this estimate
gamma	the actual sample variogram estimate
dir.hor	the horizontal direction
dir.ver	the vertical direction

id	the combined id pair

If cloud is TRUE: an object of class variogramCloud, with the field np encoding the numbers of the point pair that contributed to a variogram cloud estimate, as follows. The first point is found by 1 + the integer division of np by the .BigInt attribute of the returned object, the second point by 1 + the remainder of that division. as.data.frame.variogramCloud returns no np field, but does the decoding into:

left	for variogramCloud: data id (row number) of one of the data pair
right	for variogramCloud: data id (row number) of the other data in the pair

In case of a spatio-temporal variogram is sought see variogramST for details.

Note

variogram.default should not be called by users directly, as it makes many assumptions about the organization of the data, that are not fully documented (but of course, can be understood from reading the source code of the other variogram methods)

Successfully setting gridded() <- TRUE may trigger a branch that will fail unless dx and dy are identical, and not merely similar to within machine epsilon.

Author(s)

Edzer Pebesma

References

Cressie, N.A.C., 1993, Statistics for Spatial Data, Wiley.

Cressie, N., C. Wikle, 2011, Statistics for Spatio-temporal Data, Wiley.

Pebesma, E.J., 2004. Multivariable geostatistics in S: the gstat package. Computers and Geosciences, 30: 683-691.

See Also

print.gstatVariogram, plot.gstatVariogram, plot.variogramCloud; for variogram models: vgm, to fit a variogram model to a sample variogram: fit.variogram variogramST for details on the spatio-temporal sample variogram.

Examples

```
library(sp)
data(meuse)
# no trend:
coordinates(meuse) = ~x+y
variogram(log(zinc)~1, meuse)
# residual variogram w.r.t. a linear trend:
variogram(log(zinc)~x+y, meuse)
# directional variogram:
variogram(log(zinc)~x+y, meuse, alpha=c(0,45,90,135))
variogram(log(zinc)~1, meuse, width=90, cutoff=1300)
```

```
# GLS residual variogram:
v = variogram(log(zinc)~x+y, meuse)
v.fit = fit.variogram(v, vgm(1, "Sph", 700, 1))
v.fit
set = list(gls=1)
v
g = gstat(NULL, "log-zinc", log(zinc)~x+y, meuse, model=v.fit, set = set)
variogram(g)

if (require(sf)) {
  proj4string(meuse) = CRS("+init=epsg:28992")
 meuse.ll = sf::st_transform(sf::st_as_sf(meuse), sf::st_crs("+proj=longlat +datum=WGS84"))
# variogram of unprojected data, using great-circle distances, returning km as units
  print(variogram(log(zinc) ~ 1, meuse.ll))
}
```

`variogramLine` *Semivariance Values For a Given Variogram Model*

Description

Generates a semivariance values given a variogram model

Usage

```
variogramLine(object, maxdist, n = 200, min = 1.0e-6 * maxdist,
 dir = c(1,0,0), covariance = FALSE, ..., dist_vector, debug.level = 0)
```

Arguments

`object`	variogram model for which we want semivariance function values
`maxdist`	maximum distance for which we want semivariance values
`n`	number of points
`min`	minimum distance; a value slightly larger than zero is usually used to avoid the discontinuity at distance zero if a nugget component is present
`dir`	direction vector: unit length vector pointing the direction in x (East-West), y (North-South) and z (Up-Down)
`covariance`	logical; if TRUE return covariance values, otherwise return semivariance values
`...`	ignored
`dist_vector`	numeric vector or matrix with distance values
`debug.level`	gstat internal debug level

Value

a data frame of dimension (n x 2), with columns distance and gamma (semivariances or covariances), or in case `dist_vector` is a matrix, a conforming matrix with semivariance/covariance values is returned.

Note

variogramLine is used to generate data for plotting a variogram model.

Author(s)

Edzer Pebesma

See Also

plot.gstatVariogram

Examples

```
variogramLine(vgm(5, "Exp", 10, 5), 10, 10)
# anisotropic variogram, plotted in E-W direction:
variogramLine(vgm(1, "Sph", 10, anis=c(0,0.5)), 10, 10)
# anisotropic variogram, plotted in N-S direction:
variogramLine(vgm(1, "Sph", 10, anis=c(0,0.5)), 10, 10, dir=c(0,1,0))
variogramLine(vgm(1, "Sph", 10, anis=c(0,0.5)), dir=c(0,1,0), dist_vector = 0.5)
variogramLine(vgm(1, "Sph", 10, anis=c(0,0.5)), dir=c(0,1,0), dist_vector = c(0, 0.5, 0.75))
```

---

variogramST *Calculate Spatio-Temporal Sample Variogram*

Description

Calculates the sample variogram from spatio-temporal data.

Usage

```
variogramST(formula, locations, data, ..., tlags = 0:15,  cutoff,
 width = cutoff/15, boundaries = seq(0, cutoff, width),
 progress = interactive(), pseudo = TRUE, assumeRegular = FALSE,
 na.omit = FALSE, cores = 1)
```

Arguments

`formula`	formula, specifying the dependent variable.
`locations`	A STFDF or STSDF containing the variable; kept for compatibility reasons with variogram, either `locations` or `data` must be provided.
`data`	A `STFDF`, `STSDF` or `STIDF` containing the variable.

...	any other arguments that will be passed to the underlying variogram function. In case of using data of type STIDF, the argument tunit is recommended (and only used in the case of STIDF) to set the temporal unit of the tlags. Additionally, twindow can be passed to control the temporal window used for temporal distance calculations. This builds on the property of xts being ordered and only the next twindow instances are considered. This avoids the need of huge temporal distance matrices. The default uses twice the number as the average difference goes into the temporal cutoff.
tlags	integer; time lags to consider or in case data is of class STIDF the actual temporal boundaries with time unit given by tunit otherwise the same unit as diff on the index of the time slot will generate is assumed.
cutoff	spatial separation distance up to which point pairs are included in semivariance estimates; as a default, the length of the diagonal of the box spanning the data is divided by three.
width	the width of subsequent distance intervals into which data point pairs are grouped for semivariance estimates, by default the cutoff is divided into 15 equal lags.
boundaries	numerical vector with distance interval upper boundaries; values should be strictly increasing
progress	logical; if TRUE, show text progress bar
pseudo	integer; use pseudo cross variogram for computing time-lagged spatial variograms? -1: find out from coordinates – if they are equal then yes, else no; 0: no; 1: yes.
assumeRegular	logical; whether the time series should be assumed regular. The first time step is assumed to be representative for the whole series. Note, that temporal lags are considered by index, and no check is made whether pairs actually have the desired separating distance.
na.omit	shall all NA values in the spatio-temporal variogram be dropped? In case where complete rows or columns in the variogram consists of NA only, plot might produce a distorted picture.
cores	number of cores to use in parallel

Value

The spatio-temporal sample variogram contains besides the fields np, dist and gamma the spatio-temporal fields, timelag, spacelag and avgDist, the first of which indicates the time lag used, the second and third different spatial lags. spacelag is the midpoint in the spatial lag intervals as passed by the parameter boundaries, whereas avgDist is the average distance between the point pairs found in a distance interval over all temporal lags (i.e. the averages of the values dist per temporal lag.) To compute variograms for space lag h and time lag t, the pseudo cross variogram $(Z_i(s) - Z_{i+t}(s+h))^2$ is averaged over all time lagged observation sets Z_i and Z_{i+t} available (weighted by the number of pairs involved).

Author(s)

Edzer Pebesma, Benedikt Graeler

References

Cressie, N.A.C., 1993, Statistics for Spatial Data, Wiley.

Cressie, N., C. Wikle, 2011, Statistics for Spatio-temporal Data, Wiley.

Pebesma, E.J., 2004. Multivariable geostatistics in S: the gstat package. Computers and Geosciences, 30: 683-691.

See Also

plot.StVariogram, for variogram models: vgmST, to fit a spatio-temporal variogram model to a spatio-temporal sample variogram: fit.StVariogram

Examples

```
# The following spatio-temporal variogram has been calcualted through
# vv = variogram(PM10~1, r5to10, width=20, cutoff = 200, tlags=0:5)
# in the vignette "st".

data(vv)
str(vv)
plot(vv)
```

---

variogramSurface *Semivariance values for a given spatio-temporal variogram model*

Description

Generates a surface of semivariance values given a spatio-temporal variogram model (one of separable, productSum, sumMetric, simpleSumMetric or metric)

Usage

```
variogramSurface(model, dist_grid, covariance = FALSE)
```

Arguments

model	A spatio-temporal variogram model generated through vgmST or fit.StVariogram.
dist_grid	A data.frame with two columns: spacelag and timelag.
covariance	Whether the covariance should be computed instead of the variogram (default: FALSE).

Value

A data.frame with columns spacelag, timelag and gamma.

Author(s)

Benedikt Graeler

See Also

See variogramLine for the spatial version and fit.StVariogram for the estimation of spatio-temporal variograms.

Examples

```
separableModel <- vgmST("separable",
                        space=vgm(0.86, "Exp", 476, 0.14),
                        time =vgm(   1, "Exp",   3, 0),
                        sill=113)

data(vv)

if(require(lattice)) {
plot(vv, separableModel, wireframe=TRUE, all=TRUE)
}

# plotting of sample and model variogram
plot(vv, separableModel)
```

---

vgm *Generate, or Add to Variogram Model*

Description

Generates a variogram model, or adds to an existing model. print.variogramModel prints the essence of a variogram model.

Usage

```
vgm(psill = NA, model, range = NA, nugget, add.to, anis, kappa = 0.5, ..., covtable,
 Err = 0)
## S3 method for class 'variogramModel'
print(x, ...)
## S3 method for class 'variogramModel'
plot(x, cutoff, ..., type = 'l')
as.vgm.variomodel(m)
```

Arguments

psill	(partial) sill of the variogram model component, or model: see Details
model	model type, e.g. "Exp", "Sph", "Gau", or "Mat". Can be a character vector of model types combined with c(), e.g. c("Exp", "Sph"), in which case the best fitting is returned. Calling vgm() without a model argument returns a data.frame with available models.
range	range parameter of the variogram model component; in case of anisotropy: major range

kappa	smoothness parameter for the Matern class of variogram models
nugget	nugget component of the variogram (this basically adds a nugget compontent to the model); if missing, nugget component is omitted
add.to	the variogram model to which we want to add a component (structure)
anis	anisotropy parameters: see notes below
x	a variogram model to print or plot
...	arguments that will be passed to print, e.g. digits (see examples), or to variogramLine for the plot method
covtable	if model is Tab, instead of model parameters a one-dimensional covariance table can be passed here. See covtable.R in tests directory, and example below.
Err	numeric; if larger than zero, the measurement error variance component that will not be included to the kriging equations, i.e. kriging will now smooth the process Y instead of predict the measured Z, where Z=Y+e, and Err is the variance of e
m	object of class variomodel, see **geoR**
cutoff	maximum distance up to which variogram values are computed
type	plot type

Details

If only the first argument (psill) is given a character value/vector indicating one or more models, as in vgm("Sph"), then this taken as a shorthand form of vgm(NA,"Sph",NA,NA), i.e. a spherical variogram with nugget and unknown parameter values; see examples below. Read fit.variogram to find out how NA variogram parameters are given initial values for a fitting a model, based on the sample variogram. Package automap gives further options for automated variogram modelling.

Value

If a single model is passed, an object of class variogramModel extending data.frame.

In case a vector ofmodels is passed, an object of class variogramModelList which is a list of variogramModel objects.

When called without a model argument, a data.frame with available models is returned, having two columns: short (abbreviated names, to be used as model argument: "Exp", "Sph" etc) and long (with some description).

as.vgm.variomodel tries to convert an object of class variomodel (geoR) to vgm.

Note

Geometric anisotropy can be modelled for each individual simple model by giving two or five anisotropy parameters, two for two-dimensional and five for three-dimensional data. In any case, the range defined is the range in the direction of the strongest correlation, or the major range. Anisotropy parameters define which direction this is (the main axis), and how much shorter the range is in (the) direction(s) perpendicular to this main axis.

In two dimensions, two parameters define an anisotropy ellipse, say anis = c(30, 0.5). The first parameter, 30, refers to the main axis direction: it is the angle for the principal direction of continuity (measured in degrees, clockwise from positive Y, i.e. North). The second parameter, 0.5, is the

anisotropy ratio, the ratio of the minor range to the major range (a value between 0 and 1). So, in our example, if the range in the major direction (North-East) is 100, the range in the minor direction (South-East) is 0.5 x 100 = 50.

In three dimensions, five values should be given in the form `anis = c(p,q,r,s,t)`. Now, p is the angle for the principal direction of continuity (measured in degrees, clockwise from Y, in direction of X), q is the dip angle for the principal direction of continuity (measured in positive degrees up from horizontal), r is the third rotation angle to rotate the two minor directions around the principal direction defined by p and q. A positive angle acts counter-clockwise while looking in the principal direction. Anisotropy ratios s and t are the ratios between the major range and each of the two minor ranges. The anisotropy code was taken from GSLIB. Note that in http://www.gslib.com/sec_gb.html it is reported that this code has a bug. Quoting from this site: "The third angle in all GSLIB programs operates in the opposite direction than specified in the GSLIB book. Explanation - The books says (pp27) the angle is measured clockwise when looking toward the origin (from the postive principal direction), but it should be counter-clockwise. This is a documentation error. Although rarely used, the correct specification of the third angle is critical if used."

(Note that `anis = c(p,s)` is equivalent to `anis = c(p,0,0,s,1)`.)

The implementation in gstat for 2D and 3D anisotropy was taken from the gslib (probably 1992) code. I have seen a paper where it is argued that the 3D anisotropy code implemented in gslib (and so in gstat) is in error, but I have not corrected anything afterwards.

Author(s)

Edzer Pebesma

References

Pebesma, E.J., 2004. Multivariable geostatistics in S: the gstat package. Computers and Geosciences, 30: 683-691.

Deutsch, C.V. and Journel, A.G., 1998. GSLIB: Geostatistical software library and user's guide, second edition, Oxford University Press.

For the validity of variogram models on the sphere, see Huang, Chunfeng, Haimeng Zhang, and Scott M. Robeson. On the validity of commonly used covariance and variogram functions on the sphere. Mathematical Geosciences 43.6 (2011): 721-733.

See Also

show.vgms to view the available models, fit.variogram, variogramLine, variogram for the sample variogram.

Examples

```
vgm()
vgm("Sph")
vgm(NA, "Sph", NA, NA)
vgm(, "Sph") # "Sph" is second argument: NO nugget in this case
vgm(10, "Exp", 300)
x <- vgm(10, "Exp", 300)
```

```
vgm(10, "Nug", 0)
vgm(10, "Exp", 300, 4.5)
vgm(10, "Mat", 300, 4.5, kappa = 0.7)
vgm( 5, "Exp", 300, add.to = vgm(5, "Exp", 60, nugget = 2.5))
vgm(10, "Exp", 300, anis = c(30, 0.5))
vgm(10, "Exp", 300, anis = c(30, 10, 0, 0.5, 0.3))
# Matern variogram model:
vgm(1, "Mat", 1, kappa=.3)
x <- vgm(0.39527463, "Sph", 953.8942, nugget = 0.06105141)
x
print(x, digits = 3);
# to see all components, do
print.data.frame(x)
vv=vgm(model = "Tab",  covtable =
 variogramLine(vgm(1, "Sph", 1), 1, n=1e4, min = 0, covariance = TRUE))
vgm(c("Mat", "Sph"))
vgm(, c("Mat", "Sph")) # no nugget
```

`vgm.panel.xyplot` *panel functions for most of the variogram plots through lattice*

Description

Variogram plots contain symbols and lines; more control over them can be gained by writing your own panel functions, or extending the ones described here; see examples.

Usage

```
vgm.panel.xyplot(x, y, subscripts, type = "p", pch = plot.symbol$pch,
    col, col.line = plot.line$col, col.symbol = plot.symbol$col,
    lty = plot.line$lty, cex = plot.symbol$cex, ids, lwd = plot.line$lwd,
   model = model, direction = direction, labels, shift = shift, mode = mode, ...)
panel.pointPairs(x, y, type = "p", pch = plot.symbol$pch, col, col.line =
 plot.line$col, col.symbol = plot.symbol$col, lty = plot.line$lty,
 cex = plot.symbol$cex, lwd = plot.line$lwd, pairs = pairs,
 line.pch = line.pch, ...)
```

Arguments

`x`	x coordinates of points in this panel
`y`	y coordinates of points in this panel
`subscripts`	subscripts of points in this panel
`type`	plot type: "l" for connected lines
`pch`	plotting symbol
`col`	symbol and line color (if set)
`col.line`	line color

col.symbol	symbol color
lty	line type for variogram model
cex	symbol size
ids	gstat model ids
lwd	line width
model	variogram model
direction	direction vector c(dir.horizontal, dir.ver)
labels	labels to plot next to points
shift	amount to shift the label right of the symbol
mode	to be set by calling function only
line.pch	symbol type to be used for point of selected point pairs, e.g. to highlight point pairs with distance close to zero
pairs	two-column matrix with pair indexes to be highlighted
...	parameters that get passed to lpoints

Value

ignored; the enclosing function returns a plot of class trellis

Author(s)

Edzer Pebesma

See Also

plot.gstatVariogram, vgm

Examples

```
library(sp)
data(meuse)
coordinates(meuse) <- c("x", "y")
library(lattice)
mypanel = function(x,y,...) {
 vgm.panel.xyplot(x,y,...)
 panel.abline(h=var(log(meuse$zinc)), color = 'red')
}
plot(variogram(log(zinc)~1,meuse), panel = mypanel)
```

vgmArea *point-point, point-area or area-area semivariance*

Description

Compute point-point, point-area or area-area variogram values from point model

Usage

```
vgmArea(x, y = x, vgm, ndiscr = 16, verbose = FALSE, covariance = TRUE)
```

Arguments

x	object of class SpatialPoints or SpatialPolygons
y	object of class SpatialPoints or SpatialPolygons
vgm	variogram model, see vgm
ndiscr	number of points to discretize an area, using spsample
verbose	give progress bar
covariance	logical; compute covariances, rather than semivariances?

Value

semivariance or covariance matrix of dimension `length(x)` x `lenght(y)`

Author(s)

Edzer Pebesma

Examples

```
library(sp)
demo(meuse, ask = FALSE, echo = FALSE)
vgmArea(meuse[1:5,], vgm = vgm(1, "Exp", 1000)) # point-point
vgmArea(meuse[1:5,], meuse.area, vgm = vgm(1, "Exp", 1000)) # point-area
```

vgmAreaST *Function that returns the covariances for areas*

Description

Function that returns the covariances for areas based on spatio-temporal point variograms for use in the spatio-temporal area-to-point kriging

Usage

```
vgmAreaST(x, y = x, model, ndiscrSpace = 16, verbose = FALSE, covariance = TRUE)
```

Arguments

x	spatio-temporal data frame
y	spatio-temporal data frame
model	spatio-temporal variogram model for point support
ndiscrSpace	number of discretisation in space
verbose	Boolean: default to FALSE, set to TRUE for debugging
covariance	Boolean: whether the covariance shall be evaluated, currently disfunction and set to TRUE

Value

The covariance between 'x' and 'y'.

Author(s)

Benedikt Graeler

See Also

vgmArea

Examples

```
# see demo('a2pinST')
```

vgmST *Constructing a spatio-temporal variogram*

Description

Constructs a spatio-temporal variogram of a given type checking for a minimal set of parameters.

Usage

```
vgmST(stModel, ..., space, time, joint, sill, k, nugget, stAni, temporalUnit)
```

Arguments

stModel	A string identifying the spatio-temporal variogram model (see details below). Only the string before an optional "_" is used to identify the model. This mechanism can be used to identify different fits of the same model (separable_A and separable_B will be interpreted as separable models, but carry different names).
...	unused, but ensure an exact match of the following parameters.
space	A spatial variogram.
time	A temporal variogram.
joint	A joint spatio-temporal variogram.
sill	A joint spatio-temporal sill.
k	The weighting of the product in the product-sum model.
nugget	A joint spatio-temporal nugget.
stAni	A spatio-temporal anisotropy; the number of space units equivalent to one time unit.
temporalUnit	length one character vector, indicating the temporal unit (like secs)

Details

The different implemented spatio-temporal variogram models have the following required parameters (see as well the example section)

separable: A variogram for space and time each and a joint spatio-temporal sill (variograms may have a separate nugget effect, but their joint sill will be 1) generating the call

```
vgmST("separable", space, time, sill)
```

productSum: A variogram for space and time each, and the weighting of product k generating the call

```
vgmST("productSum", space, time, k)
```

sumMetric: A variogram (potentially including a nugget effect) for space, time and joint each and a spatio-temporal anisotropy ratio stAni generating the call

```
vgmST("sumMetric", space, time, joint, stAni)
```

simpleSumMetric: A variogram (without nugget effect) for `space`, `time` and `joint` each, a joint spatio-temporal `nugget` effect and a spatio-temporal anisotropy ratio `stAni` generating the call

```
vgmST("simpleSumMetric", space, time, joint, nugget, stAni)
```

metric: A spatio-temporal `joint` variogram (potentially including a nugget effect) and `stAni` generating the call

```
vgmST("metric", joint, stAni)
```

Value

Returns an S3 object of class `StVariogramModel`.

Author(s)

Benedikt Graeler

See Also

`fit.StVariogram` for fitting, `variogramSurface` to plot the variogram and `extractParNames` to better understand the parameter structure of spatio-temporal variogram models.

Examples

```
# separable model: spatial and temporal sill will be ignored
# and kept constant at 1-nugget respectively. A joint sill is used.
separableModel <- vgmST("separable",
                        space=vgm(0.9,"Exp", 147, 0.1),
                        time =vgm(0.9,"Exp", 3.5, 0.1),
                        sill=40)

# product sum model: spatial and temporal nugget will be ignored and kept
# constant at 0. Only a joint nugget is used.
prodSumModel <- vgmST("productSum",
                      space=vgm(39, "Sph", 343, 0),
                      time= vgm(36, "Exp",   3, 0),
                      k=15)

# sum metric model: spatial, temporal and joint nugget will be estimated
sumMetricModel <- vgmST("sumMetric",
                        space=vgm( 6.9, "Lin", 200, 3.0),
                        time =vgm(10.3, "Lin",  15, 3.6),
                        joint=vgm(37.2, "Exp",  84,11.7),
                        stAni=77.7)

# simplified sumMetric model, only a overall nugget is fitted. The spatial,
# temporal and jont nuggets are set to 0.
simpleSumMetricModel <- vgmST("simpleSumMetric",
                              space=vgm(20,"Lin", 150, 0),
                              time =vgm(20,"Lin", 10,  0),
```

```
                              joint=vgm(20,"Exp", 150, 0),
                              nugget=1, stAni=15)

# metric model
metricModel <- vgmST("metric",
                     joint=vgm(60, "Exp", 150, 10),
                     stAni=60)
```

---

vv *Precomputed variogram for PM10 in data set air*

Description

Precomputed variogram for PM10 in data set air

Usage

```
data(vv)
```

Format

data set structure is explained in variogramST.

Examples

```
## Not run:
# obtained by:
library(spacetime)
library(gstat)
data(air)
suppressWarnings(proj4string(stations) <- CRS(proj4string(stations)))
rural = STFDF(stations, dates, data.frame(PM10 = as.vector(air)))
rr = rural[,"2005::2010"]
unsel = which(apply(as(rr, "xts"), 2, function(x) all(is.na(x))))
r5to10 = rr[-unsel,]
vv = variogram(PM10~1, r5to10, width=20, cutoff = 200, tlags=0:5)

## End(Not run)
```

walker *Walker Lake sample and exhaustive data sets*

Description

This is the Walker Lake data sets (sample and exhaustive data set), used in Isaaks and Srivastava's Applied Geostatistics.

Usage

```
data(walker)
```

Format

This data frame contains the following columns:

Id Identification Number

X Xlocation in meter

Y Ylocation in meter

V V variable, concentration in ppm

U U variable, concentration in ppm

T T variable, indicator variable

Note

This data sets was obtained from the data sets on ai-geostats (link no longer functioning)

References

Applied Geostatistics by Edward H. Isaaks, R. Mohan Srivastava; Oxford University Press.

Examples

```
library(sp)
data(walker)
summary(walker)
summary(walker.exh)
```

`wind` *Ireland wind data, 1961-1978*

Description

Daily average wind speeds for 1961-1978 at 12 synoptic meteorological stations in the Republic of Ireland (Haslett and raftery 1989). Wind speeds are in knots (1 knot = 0.5418 m/s), at each of the stations in the order given in Fig.4 of Haslett and Raftery (1989, see below)

Usage

```
data(wind)
```

Format

data.frame `wind` contains the following columns:

year year, minus 1900

month month (number) of the year

day day

RPT average wind speed in knots at station RPT

VAL average wind speed in knots at station VAL

ROS average wind speed in knots at station ROS

KIL average wind speed in knots at station KIL

SHA average wind speed in knots at station SHA

BIR average wind speed in knots at station BIR

DUB average wind speed in knots at station DUB

CLA average wind speed in knots at station CLA

MUL average wind speed in knots at station MUL

CLO average wind speed in knots at station CLO

BEL average wind speed in knots at station BEL

MAL average wind speed in knots at station MAL

data.frame `wind.loc` contains the following columns:

Station Station name

Code Station code

Latitude Latitude, in DMS, see examples below

Longitude Longitude, in DMS, see examples below

MeanWind mean wind for each station, metres per second

Note

This data set comes with the following message: "Be aware that the dataset is 532494 bytes long (thats over half a Megabyte). Please be sure you want the data before you request it."

The data were obtained on Oct 12, 2008, from: http://www.stat.washington.edu/raftery/software.html The data are also available from statlib.

Locations of 11 of the stations (ROS, Rosslare has been thrown out because it fits poorly the spatial correlations of the other stations) were obtained from: http://www.stat.washington.edu/research/reports/2005/tr475.pdf

Roslare lat/lon was obtained from google maps, location Roslare. The mean wind value for Roslare comes from Fig. 1 in the original paper.

Haslett and Raftery proposed to use a sqrt-transform to stabilize the variance.

Author(s)

Adrian Raftery; imported to R by Edzer Pebesma

References

These data were analyzed in detail in the following article:

Haslett, J. and Raftery, A. E. (1989). Space-time Modelling with Long-memory Dependence: Assessing Ireland's Wind Power Resource (with Discussion). Applied Statistics 38, 1-50.

and in many later papers on space-time analysis, for example:

Tilmann Gneiting, Marc G. Genton, Peter Guttorp: Geostatistical Space-Time Models, Stationarity, Separability and Full symmetry. Ch. 4 in: B. Finkenstaedt, L. Held, V. Isham, Statistical Methods for Spatio-Temporal Systems.

Examples

```
data(wind)
summary(wind)
wind.loc
library(sp) # char2dms
wind.loc$y = as.numeric(char2dms(as.character(wind.loc[["Latitude"]])))
wind.loc$x = as.numeric(char2dms(as.character(wind.loc[["Longitude"]])))
coordinates(wind.loc) = ~x+y

## Not run:
# fig 1:
library(maps)
library(mapdata)
map("worldHires", xlim = c(-11,-5.4), ylim = c(51,55.5))
points(wind.loc, pch=16)
text(coordinates(wind.loc), pos=1, label=wind.loc$Station)

## End(Not run)

wind$time = ISOdate(wind$year+1900, wind$month, wind$day)
# time series of e.g. Dublin data:
plot(DUB~time, wind, type= 'l', ylab = "windspeed (knots)", main = "Dublin")
```

```
# fig 2:
#wind = wind[!(wind$month == 2 & wind$day == 29),]
wind$jday = as.numeric(format(wind$time, '%j'))
windsqrt = sqrt(0.5148 * as.matrix(wind[4:15]))
Jday = 1:366
windsqrt = windsqrt - mean(windsqrt)
daymeans = sapply(split(windsqrt, wind$jday), mean)
plot(daymeans ~ Jday)
lines(lowess(daymeans ~ Jday, f = 0.1))

# subtract the trend:
meanwind = lowess(daymeans ~ Jday, f = 0.1)$y[wind$jday]
velocity = apply(windsqrt, 2, function(x) { x - meanwind })

# match order of columns in wind to Code in wind.loc:
pts = coordinates(wind.loc[match(names(wind[4:15]), wind.loc$Code),])

# fig 3, but not really yet...
dists = spDists(pts, longlat=TRUE)
corv = cor(velocity)
sel = !(as.vector(dists) == 0)
plot(as.vector(corv[sel]) ~ as.vector(dists[sel]),
 xlim = c(0,500), ylim = c(.4, 1), xlab = "distance (km.)",
 ylab = "correlation")
# plots all points twice, ignores zero distance
# now really get fig 3:
ros = rownames(corv) == "ROS"
dists.nr = dists[!ros,!ros]
corv.nr = corv[!ros,!ros]
sel = !(as.vector(dists.nr) == 0)
plot(as.vector(corv.nr[sel]) ~ as.vector(dists.nr[sel]), pch = 3,
 xlim = c(0,500), ylim = c(.4, 1), xlab = "distance (km.)",
 ylab = "correlation")
# add outlier:
points(corv[ros,!ros] ~ dists[ros,!ros], pch=16, cex=.5)
xdiscr = 1:500
# add correlation model:
lines(xdiscr, .968 * exp(- .00134 * xdiscr))
```

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