

# Package ‘geospt’

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**Type** Package

**Title** Geostatistical Analysis and Design of Optimal Spatial Sampling Networks

**Version** 1.0-2

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**Imports** limSolve, fields, gsl, plyr, TeachingDemos, sgeostat, grDevices, stats, methods, graphics, utils

**Description** Estimation of the variogram through trimmed mean, radial basis functions (optimization, prediction and cross-validation), summary statistics from cross-validation, pocket plot, and design of optimal sampling networks through sequential and simultaneous points methods.

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geospt-package	<i>Geostatistical Analysis and Design of Optimal Spatial Sampling Networks</i>
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## Description

A set of functions for: estimation of the variogram through trimmed mean, radial basis functions (optimization, prediction and cross-validation), summary statistics from cross-validation, pocket plot, and design of optimal sampling networks through sequential and simultaneous points methods

## Details

Package:	geospt
Type:	Package
Version:	1.0-2
Date:	2015-08-12
License:	GPL (>= 2)
LazyLoad:	yes

## Author(s)

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**See Also**

[rbf](#), [est.variograms](#), [seqPtsOptNet](#), [simPtsOptNet](#)

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bestnet	<i>Generate a SpatialPoints object corresponding to the best result obtained in an optimized network</i>
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---

**Description**

Generate a SpatialPoints object with the  $x$  and  $y$  coordinates corresponding to the best result obtained in an optimized network. The parameter to be passed to this function must be the result of [seqPtsOptNet](#) or [simPtsOptNet](#)

**Usage**

```
bestnet(optimnet)
```

**Arguments**

optimnet      object of class `rbga` resulting from [seqPtsOptNet](#) or [simPtsOptNet](#)

**Value**

a SpatialPoints object

**See Also**

See function [rbga](#) in the `genalg` package; for examples see [seqPtsOptNet](#) and [simPtsOptNet](#)

---

`bp.with.outlier.label` *geospt internal function*

---

**Description**

geospt internal function

**Note**

This function is not meant to be called by users directly

COSha10

*Soil organic carbon database at a sampling depth of 0-10 cm***Description**

Soil organic carbon database of samples taken in several soil and land cover types at La Libertad Research Center at a sampling depth of 0-10 cm

**Usage**

data(COSha10)

**Format**

A data frame with 122 observations on the following 10 variables:

ID ID of each sampling site

x *x*-coordinate of each site. Spatial reference system: UTM 18N

y *y*-coordinate of each site. Spatial reference system: UTM 18N

DA10 measured soil bulk density ( $\text{g cm}^{-3}$ )

CO10 measured soil carbon concentration (%)

COB1r land cover at each sampling site in 2007. See details below

S\_UDS soil type at each sampling site. See details below

COSha10 calculated total soil carbon stock ( $\text{t ha}^{-1}$ ). See details below

Cor4DAidep total soil carbon stock ( $\text{t ha}^{-1}$ ) corrected by soil compaction factors

CorT corrected total soil carbon stock with Box-Cox transformation applied

**Details**

A total of 150 samples for a 0-10 cm depth was collected and analyzed for soil bulk density and organic carbon concentration in 2007 at La Libertad Research Center in Villavicencio, Colombia. The samples were taken in soils under different land cover types: rice crops (Az), citrus crops (Ci), forest plantations (Cpf), annual crops (Ctv), grasses (P), and oil palm crops (P1). In the soil type names, the first two letters correspond to the short name of the soil series, the lower-case letters indicate the slope class, and the number denotes the type of soil drainage.

Total soil carbon stock *COSha* was calculated as follows (Guo & Gifford, 2002):

$$COSha = DA * CO * d$$

where *DA* is soil bulk density ( $\text{g cm}^{-3}$ ), *CO* is soil organic carbon concentration (%) and *d* is sampling depth (cm).

Given that the data did not fit a normal distribution, a Box-Cox transformation was applied (Box & Cox, 1964). Some samples were discarded for the design of sampling networks. The complete database and description can be found in Santacruz (2010) and in Santacruz et al., (2014).

**Source**

Santacruz, A. 2010. *Design of optimal spatial sampling networks for the monitoring of soil organic carbon at La Libertad Research Center through the application of genetic algorithms*. M.Sc. Thesis. National University of Colombia, Bogotá. 162 p. (In Spanish)

**References**

Santacruz, A., Rubiano, Y., Melo, C., 2014. *Evolutionary optimization of spatial sampling networks designed for the monitoring of soil carbon*. In: Hartemink, A., McSweeney, K. (Eds.). *Soil Carbon. Series: Progress in Soil Science*. (pp. 77-84). Springer. [\[link\]](#)

Santacruz, A., 2011. *Evolutionary optimization of spatial sampling networks. An application of genetic algorithms and geostatistics for the monitoring of soil organic carbon*. Editorial Académica Española. 183 p. ISBN: 978-3-8454-9815-7 (In Spanish) [\[link\]](#)

Guo, L., Gifford, R., 2002. *Soil carbon stocks and land use change: a meta analysis*. *Global Change Biology* 8, 345-360.

Box, G., Cox, D., 1964. *An analysis of transformations*. *Journal of the Royal Statistical Society. Series B (Methodological)* 26 (2), 211-252.

**See Also**

[COSha10map](#)

**Examples**

```
data(COSha10)
str(COSha10)
```

---

COSha10map

*Map of total soil carbon stock (t/ha) at 0-10 cm depth*

---

**Description**

Map of total soil carbon stock ( $\text{t ha}^{-1}$ ) at 0-10 cm depth at La Libertad Research Center. The map was obtained through ordinary kriging interpolation. Spatial reference system: UTM 18N

**Usage**

```
data(COSha10map)
```

**Format**

The format is: Formal class 'SpatialPixelsDataFrame' [package "sp"]

**Source**

Santacruz, A., 2010. *Design of optimal spatial sampling networks for the monitoring of soil organic carbon at La Libertad Research Center through the application of genetic algorithms*. M.Sc. Thesis. National University of Colombia, Bogotá. 162 p. (In Spanish)

## References

Santacruz, A., Rubiano, Y., Melo, C., 2014. *Evolutionary optimization of spatial sampling networks designed for the monitoring of soil carbon*. In: Hartemink, A., McSweeney, K. (Eds.). *Soil Carbon. Series: Progress in Soil Science*. (pp. 77-84). Springer. [\[link\]](#)

Santacruz, A., 2011. *Evolutionary optimization of spatial sampling networks. An application of genetic algorithms and geostatistics for the monitoring of soil organic carbon*. Editorial Académica Española. 183 p. ISBN: 978-3-8454-9815-7 (In Spanish) [\[link\]](#)

## See Also

[COSha10](#)

## Examples

```
data(COSha10map)
data(lalib)
summary(COSha10map)
l1 = list("sp.polygons", lalib)
spplot(COSha10map, "var1.pred", main="Soil carbon stock (t/ha) at 0-10 cm depth",
       col.regions=bpy.colors(100), scales = list(draw =TRUE), xlab ="East (m)",
       ylab = "North (m)", sp.layout=list(l1))
```

---

COSha30

*Soil organic carbon database at a sampling depth of 0-30 cm*

---

## Description

Soil organic carbon database of samples taken in several soil and land cover types at La Libertad Research Center at a sampling depth of 0-30 cm

## Usage

```
data(COSha30)
```

## Format

A data frame with 118 observations on the following 10 variables:

ID ID of each sampling site

x x-coordinate of each site. Spatial reference system: UTM 18N

y y-coordinate of each site. Spatial reference system: UTM 18N

DA30 measured soil bulk density ( $\text{g cm}^{-3}$ )

CO30 measured soil carbon concentration (%)

COB1r land cover at each sampling site in 2007. See details below

S\_UDS soil type at each sampling site. See details below

COSha30 calculated total soil carbon stock ( $\text{t ha}^{-1}$ ). See details below

Cor4DAi dep total soil carbon stock ( $\text{t ha}^{-1}$ ) corrected by soil compaction factors

CorT corrected total soil carbon stock with Box-Cox transformation applied

## Details

A total of 150 samples for a 0-30 cm depth was collected and analyzed for soil bulk density and organic carbon concentration in 2007 at La Libertad Research Center in Villavicencio, Colombia. The samples were taken in soils under different land cover types: rice crops (Az), citrus crops (Ci), forest plantations (Cpf), annual crops (Ctv), grasses (P), and oil palm crops (P1). In the soil type names, the first two letters correspond to the short name of the soil series, the lower-case letters indicate the slope class, and the number denotes the type of soil drainage.

Total soil carbon stock *COSha* was calculated as follows (Guo & Gifford, 2002):

$$COSha = DA * CO * d$$

where *DA* is soil bulk density ( $\text{g cm}^{-3}$ ), *CO* is soil organic carbon concentration (%) and *d* is sampling depth (cm).

Given that the data did not fit a normal distribution, a Box-Cox transformation was applied (Box & Cox, 1964). Some samples were discarded for the design of sampling networks. The complete database and description can be found in Santacruz (2010) and in Santacruz et al., (2014).

## Source

Santacruz, A. 2010. *Design of optimal spatial sampling networks for the monitoring of soil organic carbon at La Libertad Research Center through the application of genetic algorithms*. M.Sc. Thesis. National University of Colombia, Bogotá. 162 p. (In Spanish)

## References

- Santacruz, A., Rubiano, Y., Melo, C., 2014. *Evolutionary optimization of spatial sampling networks designed for the monitoring of soil carbon*. In: Hartemink, A., McSweeney, K. (Eds.). *Soil Carbon. Series: Progress in Soil Science*. (pp. 77-84). Springer. [\[link\]](#)
- Santacruz, A., 2011. *Evolutionary optimization of spatial sampling networks. An application of genetic algorithms and geostatistics for the monitoring of soil organic carbon*. Editorial Académica Española. 183 p. ISBN: 978-3-8454-9815-7 (In Spanish) [\[link\]](#)
- Guo, L., Gifford, R., 2002. *Soil carbon stocks and land use change: a meta analysis*. *Global Change Biology* 8, 345-360.
- Box, G., Cox, D., 1964. *An analysis of transformations*. *Journal of the Royal Statistical Society. Series B (Methodological)* 26 (2), 211-252.

## See Also

[COSha30map](#)

## Examples

```
data(COSha30)
str(COSha30)
```

---

`COSha30map`*Map of total soil carbon stock (t/ha) at 0-30 cm depth*

---

### Description

Map of total soil carbon stock ( $\text{t ha}^{-1}$ ) at 0-30 cm depth at La Libertad Research Center. The map was obtained through ordinary kriging interpolation. Spatial reference system: UTM 18N

### Usage

```
data(COSha30map)
```

### Format

The format is: Formal class 'SpatialPixelsDataFrame' [package "sp"]

### Source

Santacruz, A., 2010. *Design of optimal spatial sampling networks for the monitoring of soil organic carbon at La Libertad Research Center through the application of genetic algorithms*. M.Sc. Thesis. National University of Colombia, Bogotá. 162 p. (In Spanish)

### References

Santacruz, A., Rubiano, Y., Melo, C., 2014. *Evolutionary optimization of spatial sampling networks designed for the monitoring of soil carbon*. In: Hartemink, A., McSweeney, K. (Eds.). *Soil Carbon. Series: Progress in Soil Science*. (pp. 77-84). Springer. [\[link\]](#)

Santacruz, A., 2011. *Evolutionary optimization of spatial sampling networks. An application of genetic algorithms and geostatistics for the monitoring of soil organic carbon*. Editorial Académica Española. 183 p. ISBN: 978-3-8454-9815-7 (In Spanish) [\[link\]](#)

### See Also

[COSha30](#)

### Examples

```
data(COSha30map)
data(lalib)
summary(COSha30map)
l1 = list("sp.polygons", lalib)
spplot(COSha30map, "var1.pred", main="Soil carbon stock (t/ha) at 0-30 cm depth",
       col.regions=bpy.colors(100), scales = list(draw =TRUE), xlab = "East (m)",
       ylab = "North (m)", sp.layout=list(l1))
```



**Description**

Generate a data frame of statistical values associated with cross-validation

**Usage**

```
criterio.cv(m.cv)
```

**Arguments**

`m.cv` data frame containing: the coordinates of data, prediction columns, prediction variance of cross-validation data points, observed values, residuals, zscore (residual divided by kriging standard error), and fold. If the `rbf.tcv` function is used, the prediction variance and zscore (residual divided by standard error) will have NA's

**Value**

data frame containing: mean prediction errors (MPE), average kriging standard error (ASEPE), root-mean-square prediction errors (RMSPE), mean standardized prediction errors (MSPE), root-mean-square standardized prediction errors (RMSSPE), mean absolute percentage prediction errors (MAPPE), coefficient of correlation of the prediction errors (CCPE), coefficient of determination (R2) and squared coefficient of correlation of the prediction errors (pseudoR2)

**Examples**

```
library(gstat)
data(meuse)
coordinates(meuse) <- ~x+y
m <- vgm(.59, "Sph", 874, .04)

# leave-one-out cross validation:
out <- krige.cv(log(zinc)~1, meuse, m, nmax = 40)
criterio.cv(out)

# multiquadratic function
data(preci)
coordinates(preci) <- ~x+y

# predefined eta
tab <- rbf.tcv(prec~x+y,preci,eta=1.488733, rho=0, n.neigh=9, func="M")
criterio.cv(tab)
```

## Description

Calculate empirical variogram estimates. An object of class `variogram` contains empirical variogram estimates which are generated from a point object and a pair object. A variogram object is stored as a data frame containing seven columns: `lags`, `bins`, `classic`, `robust`, `med`, `trim` and `n`. The length of each vector is equal to the number of lags in the pair object used to create the variogram object, say `l`. The `lags` vector contains the lag numbers for each lag, beginning with one (1) and going to the number of lags (`l`). The `bins` vector contains the spatial midpoint of each lag. The `classic`, `robust`, `med` and `trimmed.mean` vectors contain: the classical, robust, median, and trimmed mean, respectively, which are given, respectively, by (see Cressie, 1993, p. 75)

classical

$$\gamma_c(h) = \frac{1}{n} \sum_{(i,j) \in N(h)} (z(x_i) - z(x_j))^2$$

robust,

$$\gamma_m(h) = \frac{(\frac{1}{n} \sum_{(i,j) \in N(h)} (\sqrt{|z(x_i) - z(x_j)|}))^4}{0.457 + \frac{0.494}{n}}$$

median

$$\gamma_{me}(h) = \frac{(\text{median}_{(i,j) \in N(h)} (\sqrt{|z(x_i) - z(x_j)|}))^4}{0.457 + \frac{0.494}{|N(h)|}}$$

and trimmed mean

$$\gamma_{tm}(h) = \frac{(\text{trimmed.mean}_{(i,j) \in N(h)} (\sqrt{|z(x_i) - z(x_j)|}))^4}{0.457 + \frac{0.494}{|N(h)|}}$$

The `n` vector contains the number  $|N(h)|$  of pairs of points in each lag  $N(h)$ .

## Usage

```
est.variograms(point.obj, pair.obj, a1, a2, trim)
```

## Arguments

<code>point.obj</code>	a point object generated by <code>point()</code>
<code>pair.obj</code>	a pair object generated by <code>pair()</code>
<code>a1</code>	a variable to calculate semivariogram for
<code>a2</code>	an optional variable name, if entered cross variograms will be created between <code>a1</code> and <code>a2</code>
<code>trim</code>	percent of trimmed mean

**Value**

A variogram object:

lags	vector of lag identifiers
bins	vector of midpoints of each lag
classic	vector of classic variogram estimates for each lag
robust	vector of robust variogram estimates for each lag
med	vector of median variogram estimates for each lag
trimmed.mean	vector of trimmed mean variogram estimates for each lag
n	vector of the number of pairs in each lag

**Note**

Based on the [est.variogram](#) function of the `sgeostat` package

**References**

Bardossy, A., 2001. *Introduction to Geostatistics*. University of Stuttgart.

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

Majure, J., Gebhardt, A., 2009. `sgeostat`: An Object-oriented Framework for Geostatistical Modeling in S+. R package version 1.0-23.

Roustant O., Dupuy, D., Helbert, C., 2007. *Robust Estimation of the Variogram in Computer Experiments*. Ecole des Mines, Département 3MI, 158 Cours Fauriel, 42023 Saint-Etienne, France

**See Also**

[point](#), [pair](#)

**Examples**

```
library(sgeostat, pos=which(search()=="package:gstat")+1)
data(maas)
maas.point <- point(maas)
maas.pair <- pair(maas.point, num.lags=24, maxdist=2000)
maas.v <- est.variograms(maas.point,maas.pair,'zinc',trim=0.1)
maas.v
```

---

extractFormula

*geospt internal function*

---

**Description**

geospt internal function

**Note**

This function is not meant to be called by users directly

---

graph.rbf	<i>Graph that describes the behavior of the optimized eta and rho parameters, associated with a radial basis function</i>
-----------	---

---

### Description

Function for plotting the RMSPE for several values of the smoothing parameter  $\eta$  with the same dataset. A curve is fitted to the points, and then the optimal  $\eta$  that provides the smallest RMSPE is determined from the curve, by the `optimize` function from the stats package.

### Usage

```
graph.rbf(formula, data, eta.opt, rho.opt, n.neigh, func, np, x0, eta.dmax,
rho.dmax, P.T, iter, ...)
```

### Arguments

formula	formula that defines the dependent variable as a linear model of independent variables; suppose the dependent variable has name $z$ , for a <i>rbf</i> detrended use $z \sim I$ ; for a <i>rbf</i> with trend, suppose $z$ is linearly dependent on $x$ and $y$ , use the formula $z \sim x + y$ (linear trend).
data	SpatialPointsDataFrame: should contain the dependent variable, independent variables, and coordinates.
eta.opt	logical, indicating whether the parameter $\eta$ should be regarded as fixed (eta.opt = FALSE) or should be estimated (eta.opt = TRUE)
rho.opt	logical, indicating whether the parameter $\rho$ should be regarded as fixed (rho.opt = FALSE) or should be estimated (rho.opt = TRUE)
n.neigh	number of nearest observations that should be used for a <i>rbf</i> prediction, where nearest is defined in terms of the spatial locations
func	function to be optimized. The following radial basis function model types are currently available: gaussian "GAU", exponential "EXPON", trigonometric "TRI", thin plate spline "TPS", completely regularized spline "CRS", spline with tension "ST", inverse multiquadratic "IM", and multiquadratic "M", are currently available
np	number of points, where the radial basis function is calculated
x0	starting point for searching the optimum. Defaults to c(0.5, 0.5), $\eta$ and $\rho$ respectively. Use this statement only if $\eta$ and $\rho$ are equal to TRUE.
eta.dmax	maximum value of the range of the $\eta$ parameter that will be evaluated by the <code>optimize</code> function
rho.dmax	maximum value of the range of the $\rho$ parameter that will be evaluated by the <code>optimize</code> function
P.T	logical. Print Table (TRUE) or not (FALSE). Default P.T=NULL.
iter	The maximum allowed number of function evaluations.

... further parameters to be passed to the minimization functions `optimize` or `bobyqa`, typically arguments of the type `control()` which control the behavior of the minimization algorithm. See documentation about the selected minimization function for further details.

## Value

Returns a graph that describes the behavior of the optimized *eta* or *rho* parameter, and a table of values associated with the graph including optimal smoothing *eta* or *rho* parameters. If both *eta* and *rho* are FALSE simultaneously, then the function returns a list with; the best value obtained from the combinations smoothing *eta* and *rho* parameters and a lattice plot of class "trellis" with RMSPE pixel values associated with combinations of *eta* and *rho* parameters. Finally if both *eta* and *rho* are TRUE, the function will return a list with the best combination of values of the smoothing *eta* or *rho* parameters and the RMSPE associated with these.

## References

Johnston, K., Ver, J., Krivoruchko, K., Lucas, N. 2001. *Using ArcGIS Geostatistical Analysis*. ESRI.

## Examples

```
data(preci)
coordinates(preci)<--~x+y
# optimizing eta
graph.rbf(prec~1, prec, eta.opt=TRUE, rho.opt=FALSE, n.neigh=9, func="TPS",
          np=40, eta.dmax=0.2, P.T=TRUE)
## Not run:
# optimizing rho
graph.rbf(prec~x+y, prec, eta.opt=FALSE, rho.opt=TRUE, n.neigh=9, func="M",
          np=20, rho.dmax=2, P.T=TRUE)
# optimizing eta and rho
tps.lo <- graph.rbf(prec~1, prec, eta.opt=TRUE, rho.opt=TRUE, n.neigh=9, func="TPS",
                  eta.dmax=2, rho.dmax=2, x0=c(0.1,0.1), iter=40)
tps.lo$Opt # best combination of eta and rho obtained
# other optimization options
opt.u <- uobyqa(c(0.1,0.1), rbf.cv1, control = list(maxfun=40), formula=prec~1, data=prec,
              n.neigh=9, func="TPS")
opt.n <- newuoa(c(0.1,0.1), rbf.cv1, control = list(maxfun=40), formula=prec~1, data=prec,
              n.neigh=9, func="TPS")
# lattice of RMSPE values associated with a range of eta and rho, without optimization
tps.l <- graph.rbf(prec~1, prec, eta.opt=FALSE, rho.opt=FALSE, n.neigh=9, func="TPS",
                  np=10, eta.dmax=2, rho.dmax=2)
tps.l$opt.table # best combination of eta and rho obtained from lattice
tps.l$ppplot # lattice of RMSPE

## End(Not run)
```

---

`lalib`*Map of boundary enclosing La Libertad Research Center*

---

### Description

Map of boundary enclosing La Libertad Research Center

### Usage

```
data(lalib)
```

### Format

The format is: Formal class 'SpatialPolygonsDataFrame' [package "sp"]

### Details

Map of boundary enclosing La Libertad Research Center. Spatial reference system: UTM 18N

### Source

Santacruz, A. 2010. *Design of optimal spatial sampling networks for the monitoring of soil organic carbon at La Libertad Research Center through the application of genetic algorithms*. M.Sc. Thesis. National University of Colombia, Bogotá. 162 p. (In Spanish)

### References

Santacruz, A., Rubiano, Y., Melo, C., 2014. *Evolutionary optimization of spatial sampling networks designed for the monitoring of soil carbon*. In: Hartemink, A., McSweeney, K. (Eds.). *Soil Carbon. Series: Progress in Soil Science*. (pp. 77-84). Springer. [\[link\]](#)

Santacruz, A., 2011. *Evolutionary optimization of spatial sampling networks. An application of genetic algorithms and geostatistics for the monitoring of soil organic carbon*. Editorial Académica Española. 183 p. ISBN: 978-3-8454-9815-7 (In Spanish) [\[link\]](#)

### Examples

```
data(lalib)
summary(lalib)
plot(lalib)
```

network.design

*Generating ASEPE associated with a conditioned network design***Description**

Generates a sampling network for a given sampling distance or type (configuration), and calculates the average kriging standard error prediction errors (ASEPE) associated with the spatial configuration for a given predefined variogram

**Usage**

```
network.design(formula, vgm.model, xmin, xmax, ymin, ymax, npoint.x, npoint.y,
npoints, boundary=NULL, type, ...)
```

**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 $z \sim 1$ ; for simple kriging also define beta (see below); for universal kriging, suppose z is linearly dependent on x and y, use the formula $z \sim x + y$
vgm.model	variogram model of dependent variable (or its residuals), defined by a call to vgm or fit.variogram
npoint.x	number of points to generate on the x-axis
npoint.y	number of points to generate on the y-axis
npoints	(approximate) sample size inside (shapefile) border
xmin	minimum x-coordinate of the study area.
ymin	minimum y-coordinate of the study area.
xmax	maximum x-coordinate of the study area.
ymax	maximum y-coordinate of the study area.
boundary	SpatialPolygons or SpatialPolygonsDataFrame object
type	character; "random" for completely spatial random; "regular" for regular (systematically aligned) sampling; "stratified" for stratified random (one single random location in each "cell"); "nonaligned" for nonaligned systematic sampling (nx random y coordinates, ny random x coordinates); "hexagonal" for sampling on a hexagonal lattice; "clustered" for clustered sampling; "Fibonacci" for Fibonacci sampling on the sphere (see references). By default type ="regular".
...	further arguments will be passed of the <a href="#">krige</a> and <a href="#">spsample</a> functions.

**Value**

returns the ASEPE value associated with the spatial distribution of points and the kriging method used.

## References

Fibonacci sampling: Alvaro Gonzalez, 2010. *Measurement of Areas on a Sphere Using Fibonacci and Latitude-Longitude Lattices*. *Mathematical Geosciences* 42(1), p. 49-64

## See Also

[krige](#), [krige.cv](#), [spsample](#), [point.in.polygon](#), [sample](#)

## Examples

```
## Not run:
### regular grid 10x10
vgm1 <- vgm(112.33, "Sph", 4.3441,0)
# network: ordinary kriging (without boundary)
net1.ok <- network.design(z~1,vgm1, xmin=0,xmax=10, ymin=0, ymax=10, npoint.x=10,
  npoint.y=10, nmax=6)
net2.ok <- network.design(z~1,vgm1, xmin=0,xmax=10, ymin=0, ymax=10, npoint.x=20,
  npoint.y=20, nmax=6)
# it's worth noting that the variograms are different in each kriging,
# but for this example, the same variogram is used just to show how the function works

# network: simple kriging (without boundary)

net1.sk <- network.design(z~1,vgm1, xmin=0,xmax=10, ymin=0, ymax=10, npoint.x=10,
  npoint.y=10, nmax=6, beta=2)
net2.sk <- network.design(z~1,vgm1, xmin=0,xmax=10, ymin=0, ymax=10, npoint.x=20,
  npoint.y=20, nmax=6, beta=2)
# network: universal kriging, second order trend (without boundary)
net1.uk <- network.design(z~x + y + x*y + I(x^2)+I(y^2),vgm1, xmin=0,xmax=10, ymin=0,
  ymax=10, npoint.x=10, npoint.y=10, nmax=8)
net2.uk <- network.design(z~x + y + x*y + I(x^2)+I(y^2),vgm1, xmin=0,xmax=10, ymin=0,
  ymax=10, npoint.x=20, npoint.y=20, nmax=8)

# Creating the grid with the prediction and plotting points
library(geoR)
data(ca20)
Sr1 <- Polygon(ca20$borders)
Srs1 = Polygons(list(Sr1), "s1")
Polygon = SpatialPolygons(list(Srs1))
vgm2 <- vgm(112.33, "Sph", 15000,0)

# network: ordinary kriging (with boundary)
netb1.ok<- network.design(z~1, vgm2, npoints=50, boundary=Polygon, nmax=6)
netb2.ok<- network.design(z~1, vgm2, npoints=100, boundary=Polygon, nmax=6)
# network: simple kriging (with boundary)
netb1.sk <- network.design(z~1, vgm2, npoints=50, boundary=Polygon, nmax=6, beta=2)
netb2.sk <- network.design(z~1, vgm2, npoints=100, boundary=Polygon, nmax=6, beta=2)
# network: universal kriging, second order trend (with boundary)
netb1.uk <- network.design(z~x + y + x*y + I(x^2)+I(y^2), vgm2, npoints=50,
  boundary=Polygon, nmax=8)
netb2.uk <- network.design(z~x + y + x*y + I(x^2)+I(y^2), vgm2, npoints=100,
```



```

    boundary=Polygon, nmax=8)

## End(Not run)

```

---

pocket.plot                    *graphs the probability or standardized variance in the directions north-south or east-west*

---

### Description

The pocket-plot (so named because of its use in detecting pockets of non-stationarity) is a technique necessary to identify a localized area that is atypical with respect to the stationarity model. It is built to exploit the spatial nature of the data through the coordinates of rows and columns (east "X" and north "Y", respectively).

### Usage

```
pocket.plot(data, graph, X, Y, Z, Iden, ...)
```

### Arguments

data	data frame should contain the dependent variable and coordinates X and Y, data must be gridded
graph	type of graph associated with the probability or standardized variance plot pocket in the directions north-south or east-west; Probabilities PocketPlot by rows, ie horizontal "south-north" (PPR), Probabilities PocketPlot by columns, ie vertical "east-west" (PPC), PocketPlot of variance by rows, ie horizontal "south-north" (PVR) and PocketPlot of variance by columns, ie vertical "east-west" (PVC)
X	defined by the spatial coordinates
Y	defined by the spatial coordinates
Z	regionalized variable with which you construct the statistics associated with the probability or standardized variance, these are plotted in the so-called pocket plot
Iden	logical. The users can identify the points by themselves, TRUE or FALSE
...	arguments to be passed to ...

### Details

For identifying outliers, this function uses a modification of the `boxplot.with.outlier.label` function, available at <http://www.r-statistics.com/wp-content/uploads/2011/01/boxplot-with-outlier-label-r.txt>

### Value

returns (or plots) the pocket plot

## References

- Cressie, N.A.C. 1993. *Statistics for Spatial Data*. Wiley.
- Gomez, M., Hazen, K. 1970. *Evaluating sulfur and ash distribution in coal seams by statistical response surface regression analysis*. U.S. Bureau of Mines Report RI 7377.

## Examples

```
# Core measurements (in % coal ash) at reoriented locations.
# Units on the vertical axis are % coal ash.

# These data was found in mining samples originally reported by
# Gomez and Hazen (1970), and later used by Cressie (1993).

# These data are available in the sp and gstat packages

library(gstat)
data(coalash)
plot(coalash[,1:2], type="n", xlab="x", ylab="y")
text(coalash$x,coalash$y,coalash$coalash,cex=0.6)

# Pocket plot in the north-south direction.
# Units on the vertical axis are root (% coal ash)

# Plot generated with the function pocket.plot
# Clearly rows 2, 6, and 8 are atypical

# This serves as verification that these rows are potentially problematic

# Analysis of local stationarity in probabilities of the coal in south-north direction
pocket.plot(coalash, "PPR", coalash$x, coalash$y, coalash$coalash, FALSE)

# Analysis of local stationarity in variance of the coal in south-north direction
pocket.plot(coalash, "PVR", coalash$x, coalash$y, coalash$coalash, FALSE)

# Analysis of local stationarity in probabilities of the coal in east-west direction
pocket.plot(coalash, "PPC", coalash$x, coalash$y, coalash$coalash, FALSE)

# Analysis of local stationarity in variance of the coal in east-west direction
pocket.plot(coalash, "PVC", coalash$x, coalash$y, coalash$coalash, FALSE)
```

---

```
preci
```

```
Empirical data related to rainfall
```

---

## Description

Empirically generated data in 10 arbitrary locations associated with the rainfall variable

**Usage**

```
data(preci)
```

**Format**

A data frame with 10 observations on the following 4 variables:

Obs a numeric vector; observation number

x a numeric vector; x-coordinate; unknown reference

y a numeric vector; y-coordinate; unknown reference

prec a numeric vector; the target variable

**Examples**

```
data(preci)
summary(preci)
```

---

rbf	<i>gaussian, exponential, trigonometric, thin plate spline, inverse multi-quadratic, and multiquadratic radial basis function prediction</i>
-----	--

---

**Description**

Function for gaussian (GAU), exponential (EXPON), trigonometric (TRI), thin plate spline (TPS), completely regularized spline (CRS), spline with tension (ST), inverse multiquadratic (IM), and multiquadratic (M) radial basis function (*rbf*), where *rbf* is in a local neighbourhood

**Usage**

```
rbf(formula, data, eta, rho, newdata, n.neigh, func)
```

**Arguments**

formula	formula that defines the dependent variable as a linear model of independent variables; suppose the dependent variable has name z, for a <i>rbf</i> detrended use $z \sim 1$ , for a <i>rbf</i> with trend, suppose z is linearly dependent on x and y, use the formula $z \sim x + y$ (linear trend).
data	SpatialPointsDataFrame: should contain the dependent variable, independent variables, and coordinates.
eta	the optimal smoothing parameter, we recommend using the parameter found by minimizing the root-mean-square prediction errors using cross-validation
rho	the optimal parameter robustness, we recommend using the parameter found by minimizing the root-mean-square prediction errors using cross-validation. eta and rho parameters can be optimized simultaneously, through the <a href="#">bobyqa</a> function from <code>nloptr</code> or <code>minqa</code> packages

newdata	data frame or spatial object with prediction/simulation locations; should contain attribute columns with the independent variables (if present) and (if locations is a formula) the coordinates with names, as defined in locations where you want to generate new predictions
n.neigh	number of nearest observations that should be used for a <i>rbf</i> prediction, where nearest is defined in terms of the spatial locations
func	radial basis function model type, e.g. "GAU", "EXPON", "TRI", "TPS", "CRS", "ST", "IM" and "M", are currently available

### Details

rbf function generates individual predictions from gaussian (GAU), exponential (EXPON), trigonometric (TRI) thin plate spline (TPS), completely regularized spline (CRS), spline with tension (ST), inverse multiquadratic (IM), and multiquadratic (M) functions

### Value

Attributes columns contain coordinates, predictions, and the variance column contains NA's

### Examples

```
data(preci)
coordinates(preci) <- ~x+y

# prediction case: one point
point <- data.frame(3,4)
names(point) <- c("x","y")
coordinates(point) <- ~x+y
rbf(prec~x+y, prec, eta=0.1460814, rho=0, newdata=point,n.neigh=10, func="TPS")

# prediction case: a grid of points
puntos<-expand.grid(x=seq(min(preci$x),max(preci$x),0.05), y=seq(min(preci$y),
max(preci$y),0.05))
coordinates(puntos) <- ~x+y
pred.rbf <- rbf(prec~x+y, prec, eta=0.1460814, rho=0, newdata=puntos, n.neigh=10, func="TPS")
coordinates(pred.rbf) = c("x", "y")
gridded(pred.rbf) <- TRUE

# show prediction map
splot(pred.rbf["var1.pred"], cuts=40, col.regions=bpy.colors(100),
main = "rainfall map TPS", key.space=list(space="right", cex=0.8))
```

---

rbf.cv

*rbf cross validation leave-one-out*


---

### Description

Generate the RMSPE value, which is given by the radial basis function with smoothing parameter eta and robustness parameter rho.

**Usage**

```
rbf.cv(formula, data, eta, rho, n.neigh, func)
```

**Arguments**

formula	formula that defines the dependent variable as a linear model of independent variables; suppose the dependent variable has name <i>z</i> , for a <i>rbf</i> detrended use $z \sim 1$ , for a <i>rbf</i> with trend, suppose <i>z</i> is linearly dependent on <i>x</i> and <i>y</i> , use the formula $z \sim x + y$ (linear trend).
data	SpatialPointsDataFrame: should contain the dependent variable, independent variables, and coordinates.
eta	the optimal smoothing parameter; we recommend using the parameter found by minimizing the root-mean-square prediction errors using cross-validation
rho	value of optimal robustness parameter; we recommend using the parameter found by minimizing the root-mean-square prediction errors using cross-validation. <i>eta</i> and <i>rho</i> parameters can be optimized simultaneously, through the <a href="#">bobyqa</a> function from <code>nloptr</code> or <code>minqa</code> packages
n.neigh	number of nearest observations that should be used for a <i>rbf</i> prediction, where nearest is defined in terms of the spatial locations
func	radial basis function model type, e.g. "GAU", "EXPON", "TRI", "TPS", "CRS", "ST", "IM" and "M", are currently available

**Value**

returns the RMSPE value

**See Also**

[rbf](#)

**Examples**

```
data(preci)
coordinates(preci) <- ~x+y
rbf.cv(prec~1, prec, eta=0.2589, rho=0, n.neigh=9, func="M")
```

---

```
rbf.cv1
```

*Generates a RMSPE value, result of cross validation leave-one-out*

---

**Description**

Generate the RMSPE value, which is given by the radial basis function with smoothing parameter *eta* and robustness parameter *rho*.

**Usage**

```
rbf.cv1(param, formula, data, n.neigh, func)
```

**Arguments**

param	vector starting points ( <i>eta</i> and <i>rho</i> respectively) for searching the <i>RMSPE</i> optimum.
formula	formula that defines the dependent variable as a linear model of independent variables; suppose the dependent variable has name <i>z</i> , for a <i>rbf</i> detrended use $z \sim I$ , for a <i>rbf</i> with trend, suppose <i>z</i> is linearly dependent on <i>x</i> and <i>y</i> , use the formula $z \sim x + y$ (linear trend).
data	SpatialPointsDataFrame: should contain the dependent variable, independent variables, and coordinates.
n.neigh	number of nearest observations that should be used for a <i>rbf</i> prediction, where nearest is defined in terms of the spatial locations
func	radial basis function model type, e.g. "GAU", "EXPON", "TRI", "TPS", "CRS", "ST", "IM" and "M", are currently available

**Value**

returns the RMSPE value

**See Also**

[rbf](#)

**Examples**

```
## Not run:
data(preci)
coordinates(preci) <- ~x+y
bobyqa(c(0.5, 0.5), rbf.cv1, lower=c(1e-05,0), upper=c(2,2), formula=prec~x+y, data=preci,
  n.neigh=9, func="TRI")
# obtained with the optimal values previously estimated
rbf.cv1(c(0.2126191,0.1454171), prec~x+y, preci, n.neigh=9, func="TRI")

## End(Not run)
```

---

RBF.phi

*radial basis function evaluation*


---

**Description**

generate the value associated with radial basis functions; gaussian (GAU), exponential (EXPON), trigonometric (TRI), thin plate spline (TPS), completely regularized spline (CRS), spline with tension (ST), inverse multiquadratic (IM), and multiquadratic (M)

**Usage**

```
RBF.phi(distance, eta, func)
```

**Arguments**

distance	corresponds to the Euclidean distance between two points in space
eta	the optimal smoothing parameter is found by minimizing the root-mean-square prediction errors using cross-validation
func	radial basis function model type, e.g. "GAU", "EXPON", "TRI", "TPS", "CRS", "ST", "IM" and "M", are currently available

**Value**

value obtained from the radial basis function generated with a distance, a *eta* smoothing parameter, and a function "GAU", "EXPON", "TRI", "TPS", "CRS", "ST", "IM" or "M"

**Examples**

```
data(preci)
d1 <- dist(rbind(preci[1,],preci[2,]))
RBF.phi(distance=d1, eta=0.5, func="TPS")
```

---

rbf.tcv	<i>table of rbf cross validation, leave-one-out</i>
---------	---

---

**Description**

Generates a table with the results of the evaluation of radial basis functions (*rbf*): gaussian (GAU), exponential (EXPON), trigonometric (TRI), thin plate spline (TPS), completely regularized spline (CRS), spline with tension (ST), inverse multiquadratic (IM), and multiquadratic (M) from the leave-one-out cross validation method.

**Usage**

```
rbf.tcv(formula, data, eta, rho, n.neigh, func)
```

**Arguments**

formula	formula that defines the dependent variable as a linear model of independent variables; suppose the dependent variable has name <i>z</i> , for a <i>rbf</i> detrended use $z \sim I$ , for a <i>rbf</i> with trend, suppose <i>z</i> is linearly dependent on <i>x</i> and <i>y</i> , use the formula $z \sim x + y$ (linear trend).
data	SpatialPointsDataFrame: should contain the dependent variable, independent variables, and coordinates.
eta	the optimal smoothing parameter; we recommend using the parameter found by minimizing the root-mean-square prediction errors using cross-validation
rho	value of optimal parameter robustness; we recommend using the parameter found by minimizing the root-mean-square prediction errors using cross-validation. <i>eta</i> and <i>rho</i> parameters can be optimized simultaneously, through the <a href="#">bobyqa</a> function from <code>nloptr</code> or <code>minqa</code> packages

n.neigh	number of nearest observations that should be used for a <i>rbf</i> prediction, where nearest is defined in terms of the spatial locations
func	radial basis function model type, e.g. "GAU", "EXPON", "TRI", "TPS", "CRS", "ST", "MI" and "M", are currently available

### Details

Leave-one-out cross validation (LOOCV) visits a data point, 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 rbf would otherwise predict the same value

### Value

data frame contain the data coordinates, prediction columns, observed values, residuals, the prediction variance, zscore (residual divided by standard error) which left with NA's, and the fold column which is associated to cross-validation count. Prediction columns and residuals are obtained from cross-validation data points

### See Also

[rbf](#)

### Examples

```
data(preci)
coordinates(preci)<--x+y
rbf.tcv(prec~x+y, preci, eta=0.1460814, rho=0, n.neigh=9, func="TPS")
```

---

samplePts

*sample n point locations in (or on) a spatial object*

---

### Description

sample location points within a square area, a grid, a polygon, or on a spatial line, using regular or random sampling methods. The function `spsample` from the package `sp` is used iteratively to find exactly *n* sample locations

### Usage

```
samplePts(x, n, type, ...)
```

### Arguments

x	Spatial object; see the <code>sp</code> package for details
n	exact sample size



type character; "random" for completely spatial random; "regular" for regular (systematically aligned) sampling; "stratified" for stratified random (one single random location in each "cell"); "nonaligned" for nonaligned systematic sampling (nx random y coordinates, ny random x coordinates); "hexagonal" for sampling on a hexagonal lattice; "clustered" for clustered sampling; "Fibonacci" for Fibonacci sampling on the sphere. See the sp package for details

... other arguments to be passed to spsample

### Value

an object of class `SpatialPoints-class`

### See Also

See `spsample` in the sp package

### Examples

```
data(lalib)
hexPts <- samplePts(lalib, 5, "hexagonal")
plot(lalib, xlim=c(bbox(lalib)[1], bbox(lalib)[3]), ylim=c(bbox(lalib)[2],
  bbox(lalib)[4]))
plot(hexPts, add=TRUE)
## Not run:
randomPts <- samplePts(lalib, 5, "random")
plot(lalib, xlim=c(bbox(lalib)[1], bbox(lalib)[3]), ylim=c(bbox(lalib)[2],
  bbox(lalib)[4]))
plot(randomPts, add=TRUE)

## End(Not run)
```

---

seqPtsOptNet	<i>Design of optimal sampling networks through the sequential points method</i>
--------------	---

---

### Description

Search for the optimum location of one additional point to be added to an initial network, minimizing the average standard error of kriging through a genetic algorithm. It takes, as input for the optimization, the minimum and maximum values of the coordinates that enclose the study area. This function uses previous samples information to direct additional sampling. The location of the new point is searched randomly.

### Usage

```
seqPtsOptNet(formula, loc=NULL, data, fitmodel, BLUE=FALSE, n=1, prevSeqs=NULL,
  popSize, generations, xmin, ymin, xmax, ymax, plotMap=FALSE, spMap=NULL, ...)
```

**Arguments**

formula	formula that defines the interpolation method to be used. In this parameter, a dependent variable is defined as a linear model of independent variables. Suppose the dependent variable has name $z$ , for ordinary and simple kriging use the formula $z \sim 1$ ; for simple kriging also define $\beta$ ; for universal kriging, suppose $z$ is linearly dependent on $x$ and $y$ , use the formula $z \sim x+y$ . See the <code>gstat</code> package for details
loc	object of class <code>Spatial</code> , or (deprecated) formula that defines the spatial data locations (coordinates) such as $\sim x+y$ ; see the <code>gstat</code> package for details
data	data frame containing the dependent variable, independent variables, and coordinates; see the <code>gstat</code> package for details
fitmodel	variogram model of dependent variable (or its residuals), defined by a call to <code>vgm</code> or <code>fit.variogram</code> ; see the <code>gstat</code> package for details
BLUE	logical; if TRUE return the BLUE trend estimates only, if FALSE return the BLUP predictions (kriging); see <code>predict.gstat</code> in the <code>gstat</code> package for details
n	by default, set to 1 for the sequential points method
prevSeqs	if NULL, the function finds the first optimum sequential point. Otherwise, an object of class <code>SpatialPoints</code> containing optimum points previously found must be provided
popSize	population size; see the <code>genalg</code> package for details
generations	number of iterations. Usually, hundreds or thousands are required. See the <code>genalg</code> package for details
xmin	minimum $x$ -coordinate of the study area
ymin	minimum $y$ -coordinate of the study area
xmax	maximum $x$ -coordinate of the study area
ymax	maximum $y$ -coordinate of the study area
plotMap	logical; if TRUE, the optimized spatial locations of additional points are plotted
spMap	an object of class <code>Spatial</code> ; it must be provided if <code>plotMap</code> is set to TRUE
...	other arguments to be passed to <code>gstat</code> or <code>rbga</code>

**Value**

an object of class `rbga` containing the population and the evaluation of the objective function for each chromosome in the last generation, the best and mean evaluation value in each generation, and additional information

**References**

Santacruz, A., Rubiano, Y., Melo, C., 2014. *Evolutionary optimization of spatial sampling networks designed for the monitoring of soil carbon*. In: Hartemink, A., McSweeney, K. (Eds.). *Soil Carbon. Series: Progress in Soil Science*. (pp. 77-84). Springer. [\[link\]](#)

Santacruz, A., 2011. *Evolutionary optimization of spatial sampling networks. An application of genetic algorithms and geostatistics for the monitoring of soil organic carbon*. Editorial Académica Española. 183 p. ISBN: 978-3-8454-9815-7 (In Spanish) [\[link\]](#)

Delmelle, E., 2005. *Optimization of second-phase spatial sampling using auxiliary information*. Ph.D. Thesis, Dept. Geography, State University of New York, Buffalo, NY.

## See Also

See [rbga](#) in the `genalg` package and [krige](#) in the `gstat` package

## Examples

```
## Not run:
## Load data
data(COSha10)
data(COSha10map)
data(lalib)

## Calculate the sample variogram for data, generate the variogram model and
## fit ranges and/or sills from the variogram model to the sample variogram
ve <- variogram(CorT~ 1, loc=~x+y, data=COSha10, width = 230.3647)
PSI <- 0.0005346756; RAN <- 1012.6411; NUG <- 0.0005137079
m.esf <- vgm(PSI, "Sph", RAN, NUG)
(m.f.esf <- fit.variogram(ve, m.esf))

## Optimize the location of the first additional point
## Only 15 generations are evaluated in this example (using ordinary kriging)
## Users can visualize how the location of the additional point is optimized
## if plotMap is set to TRUE
old.par <- par(no.readonly = TRUE)
par(ask=FALSE)
optpt <- seqPtsOptNet(CorT~ 1, loc=~x+y, COSha10, m.f.esf, popSize=30,
  generations=15, xmin=bbox(lalib)[1], ymin=bbox(lalib)[2], xmax=bbox(lalib)[3],
  ymax=bbox(lalib)[4], plotMap=TRUE, spMap=lalib)
par(old.par)

## Summary of the genetic algorithm results
summary(optpt, echo=TRUE)

## Graph of best and mean evaluation value of the objective function
## (average standard error) along generations
plot(optpt)

## Find and plot the best set of additional points (best chromosome) in
## the population in the last generation
(bnet1 <- bestnet(optpt))
l1 = list("sp.polygons", lalib)
l2 = list("sp.points", bnet1, col="green", pch="*", cex=5)
spplot(COSha10map, "var1.pred", main="Location of the optimized point",
  col.regions=bpy.colors(100), scales = list(draw =TRUE), xlab = "East (m)",
  ylab = "North (m)", sp.layout=list(l1,l2))
```

```

## Average standard error of the optimized sequential point
min(optpt$evaluations)

## Optimize the location of the second sequential point, taking into account
## the first one
plot(lalib)
old.par <- par(no.readonly = TRUE)
par(ask=FALSE)
optpt2 <- seqPtsOptNet(CorT~ 1, loc=~x+y, COSha10, m.f.esf, prevSeqs=bnet1,
  popSize=30, generations=15, xmin=bbox(lalib)[1], ymin=bbox(lalib)[2],
  xmax=bbox(lalib)[3], ymax=bbox(lalib)[4], plotMap=TRUE, spMap=lalib)
par(old.par)

## Find the second optimal sequential point and use it, along with the first
## one, to find another optimal sequential point, and so on iteratively

bnet2 <- bestnet(optpt2)
bnet <- rbind(bnet1, bnet2)

old.par <- par(no.readonly = TRUE)
par(ask=FALSE)
optpt3 <- seqPtsOptNet(CorT~ 1, loc=~x+y, COSha10, m.f.esf, prevSeqs=bnet,
  popSize=30, generations=25, xmin=bbox(lalib)[1], ymin=bbox(lalib)[2],
  xmax=bbox(lalib)[3], ymax=bbox(lalib)[4], plotMap=TRUE, spMap=lalib)
par(old.par)

## End(Not run)

## Multivariate prediction is also enabled:
## Not run:
ve <- variogram(CorT~ DA10, loc=~x+y, data=COSha10, width = 230.3647)
(m.f.esf <- fit.variogram(ve, m.esf))

optptMP <- seqPtsOptNet(CorT~ DA10, loc=~x+y, COSha10, m.f.esf, popSize=30,
  generations=25, xmin=bbox(lalib)[1], ymin=bbox(lalib)[2], xmax=bbox(lalib)[3],
  ymax=bbox(lalib)[4], plotMap=TRUE, spMap=lalib)

## End(Not run)

```

---

simPtsOptNet

*Design of optimal sampling networks through the simultaneous points method*


---

## Description

Search for an optimum set of simultaneous additional points to an initial network that minimize the average standard error of kriging, using a genetic algorithm. It takes, as input for the optimization, the minimum and maximum values of the coordinates that enclose the study area. This function uses previous samples information to direct additional sampling for minimum average standard error. The algorithm generates random sampling schemes.

**Usage**

```
simPtsOptNet(formula, loc=NULL, data, fitmodel, BLUE=FALSE, n, popSize,
generations, xmin, ymin, xmax, ymax, plotMap=FALSE, spMap=NULL, ...)
```

**Arguments**

formula	formula that defines the interpolation method to be used. In this parameter, a dependent variable is defined as a linear model of independent variables. Suppose the dependent variable has name $z$ , for ordinary and simple kriging use the formula $z \sim 1$ ; for simple kriging also define $\beta$ ; for universal kriging, suppose $z$ is linearly dependent on $x$ and $y$ , use the formula $z \sim x+y$ . See the <code>gstat</code> package for details
loc	object of class <code>Spatial</code> , or (deprecated) formula that defines the spatial data locations (coordinates) such as $\sim x+y$ ; see the <code>gstat</code> package for details
data	data frame containing the dependent variable, independent variables, and coordinates; see the <code>gstat</code> package for details
fitmodel	variogram model of dependent variable (or its residuals), defined by a call to <code>vgm</code> or <code>fit.variogram</code> ; see the <code>gstat</code> package for details
BLUE	logical; if TRUE return the BLUE trend estimates only, if FALSE return the BLUP predictions (kriging); see <code>predict.gstat</code> in the <code>gstat</code> package for details
n	number of additional points to be added to the original network
popSize	population size; see the <code>genalg</code> package for details
generations	number of iterations. Usually, hundreds or thousands are required. See the <code>genalg</code> package for details
xmin	minimum $x$ -coordinate of the study area
ymin	minimum $y$ -coordinate of the study area
xmax	maximum $x$ -coordinate of the study area
ymax	maximum $y$ -coordinate of the study area
plotMap	logical; if TRUE, the optimized spatial locations of additional points are plotted
spMap	an object of class <code>Spatial</code> ; it must be provided if <code>plotMap</code> is set to TRUE
...	other arguments to be passed to <code>gstat</code> or <code>rbga</code>

**Value**

an object of class `rbga` containing the population and the evaluation of the objective function for each chromosome in the last generation, the best and mean evaluation value in each generation, and additional information

**References**

Santacruz, A., Rubiano, Y., Melo, C., 2014. *Evolutionary optimization of spatial sampling networks designed for the monitoring of soil carbon*. In: Hartemink, A., McSweeney, K. (Eds.). *Soil Carbon. Series: Progress in Soil Science*. (pp. 77-84). Springer. [\[link\]](#)

Santacruz, A., 2011. *Evolutionary optimization of spatial sampling networks. An application of genetic algorithms and geostatistics for the monitoring of soil organic carbon*. Editorial Académica Española. 183 p. ISBN: 978-3-8454-9815-7 (In Spanish) [\[link\]](#)

Delmelle, E., 2005. *Optimization of second-phase spatial sampling using auxiliary information*. Ph.D. Thesis, Dept. Geography, State University of New York, Buffalo, NY.

### See Also

See [rbga](#) in the `genalg` package and [krige](#) in the `gstat` package

### Examples

```
## Not run:
## Load data
data(COSha30)
data(COSha30map)
data(lalib)

## Calculate the sample variogram for data, generate the variogram model and
## fit ranges and/or sills from the variogram model to the sample variogram
ve <- variogram(CorT~ 1, loc=~x+y, data=COSha30, width = 236.0536)
PSI <- 0.0001531892; RAN <- 1031.8884; NUG <- 0.0001471817
m.esf <- vgm(PSI, "Sph", RAN, NUG)
(m.f.esf <- fit.variogram(ve, m.esf))

## Number of additional points to be added to the network
npoints <- 5

## Optimize the location of the additional points
## Only 20 generations are evaluated in this example (using ordinary kriging)
## Users can visualize how the location of the additional points is optimized
## if plotMap is set to TRUE
old.par <- par(no.readonly = TRUE)
par(ask=FALSE)
optnets <- simPtsOptNet(CorT~ 1, loc=~x+y, COSha30, m.f.esf, n=npoints,
  popSize=30, generations=20, xmin=bbox(lalib)[1], ymin=bbox(lalib)[2],
  xmax=bbox(lalib)[3], ymax=bbox(lalib)[4], plotMap=TRUE, spMap=lalib)
par(old.par)

## Summary of the genetic algorithm results
summary(optnets, echo=TRUE)

## Graph of best and mean evaluation value of the objective function
## (average standard error) along generations
plot(optnets)

## Find and plot the best set of additional points (best chromosome) in
## the population in the last generation
(bnet <- bestnet(optnets))
l1 = list("sp.polygons", lalib)
l2 = list("sp.points", bnet, col="green", pch="*", cex=5)
splot(COSha30map, "var1.pred", main="Location of the optimized points",
```

```
col.regions=bpy.colors(100), scales = list(draw =TRUE), xlab ="East (m)",
ylab = "North (m)", sp.layout=list(l1,l2))

## Average standard error of the optimized additional points
min(optnets$evaluations)

## End(Not run)

## Multivariate prediction is also enabled:
## Not run:
ve <- variogram(CorT~ DA30, loc=~x+y, data=COSha30, width = 236.0536)
(m.f.esf <- fit.variogram(ve, m.esf))

optnetsMP <- simPtsOptNet(CorT~ DA30, loc=~x+y, COSha30, m.f.esf, n=npoints,
  popSize=30, generations=25, xmin=bbox(lalib)[1], ymin=bbox(lalib)[2],
  xmax=bbox(lalib)[3], ymax=bbox(lalib)[4], plotMap=TRUE, spMap=lalib)

## End(Not run)
```

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