

Package ‘spNNGP’

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Title Spatial Regression Models using Nearest Neighbor Gaussian Processes

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Description Fits Gaussian univariate Bayesian spatial regression models using Nearest Neighbor Gaussian Processes (NNGP).

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URL <http://blue.for.msu.edu/software.html>

Repository CRAN

NeedsCompilation yes

R topics documented:

| | |
|----------------------|---|
| spConjNNGP | 1 |
| spNNGP | 5 |
| spPredict | 8 |

| | |
|--------------|-----------|
| Index | 12 |
|--------------|-----------|

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|------------|---|
| spConjNNGP | <i>Function for fitting univariate Bayesian conjugate spatial regression models</i> |
|------------|---|

Description

The function `spConjNNGP` fits Gaussian univariate Bayesian conjugate spatial regression models using Nearest Neighbor Gaussian Processes (NNGP).

Usage

```
spConjNNGP(formula, data = parent.frame(), coords, n.neighbors = 15,
            theta.alpha, sigma.sq.IG, cov.model = "exponential",
            k.fold, score.rule,
            X.0, coords.0,
            n.omp.threads = 1, verbose=TRUE, ...)
```

Arguments

| | |
|-------------|---|
| formula | a symbolic description of the regression model to be fit. See example below. |
| data | an optional data frame containing the variables in the model. If not found in data, the variables are taken from <code>environment(formula)</code> , typically the environment from which <code>spConjNNGP</code> is called. |
| coords | an $n \times 2$ matrix of the observation coordinates in R^2 (e.g., easting and northing). |
| n.neighbors | number of neighbors used in the NNGP. |
| theta.alpha | a vector or matrix of parameter values for phi, nu, and alpha, where $\alpha = \tau^2/\sigma^2$ and nu is only required if <code>cov.model="matern"</code> . A vector is passed if you want to run the model using one set of parameters. The vector elements must be named and hold values for phi, nu, and alpha. If a matrix is passed, columns must be named and hold values for phi, alpha, and nu. Each row in the matrix defines a set of parameters for which the the model will be run. |
| sigma.sq.IG | a vector of length two that holds the hyperparameters, <i>shape</i> and <i>scale</i> respectively, for the inverse-Gamma prior on σ^2 . |
| cov.model | a quoted keyword that specifies the covariance function used to model the spatial dependence structure among the observations. Supported covariance model key words are: "exponential", "matern", "spherical", and "gaussian". See below for details. |
| k.fold | an optional argument used to specify the number of k folds for cross-validation. In k -fold cross-validation, the data specified in <code>model</code> is randomly partitioned into k equal sized subsamples. Of the k subsamples, $k-1$ subsamples are used to fit the model and the remaining k samples are used for prediction. The cross-validation process is repeated k times (the folds). Root mean squared prediction error (RMSPE) and continuous ranked probability score (CRPS; Gneiting and Raftery, 2007) rules are averaged over the k fold prediction results and reported for the parameter set(s) defined by <code>theta.alpha</code> . The parameter set that yields the <i>best</i> performance based on the scoring rule defined by <code>score.rule</code> is used fit the final model that uses all the data and make predictions if <code>X.0</code> and <code>coords.0</code> are specified. Results from the k -fold cross-validation are returned in the <code>k.fold.scores</code> matrix. |
| score.rule | a quoted keyword "rmspe" or "crps" that specifies the scoring rule used to select the <i>best</i> parameter set, see argument definition for <code>k.fold</code> for more details. |
| X.0 | the design matrix for prediction locations. An intercept should be provided in the first column if one is specified in <code>model</code> . |
| coords.0 | the spatial coordinates corresponding to <code>X.0</code> . |

| | |
|---------------|--|
| n.omp.threads | a positive integer indicating the number of threads to use for SMP parallel processing. The package must be compiled for OpenMP support. For most Intel-based machines, we recommend setting n.omp.threads to up to the number of hyperthreaded cores. |
| verbose | if TRUE, model specification and progress of the sampler is printed to the screen. Otherwise, nothing is printed to the screen. |
| ... | currently no additional arguments. |

Value

An object of class cNNGP, which is a list comprising:

| | |
|---------------------|---|
| beta.hat | a matrix of regression coefficient estimates corresponding to parameter set(s) defined in theta.alpha. |
| theta.alpha.sigmaSq | the theta.alpha vector or matrix with σ^2 estimates appended. |
| k.fold.scores | results from the k-fold cross-validation if k.fold is specified. |
| y.0.hat | prediction if X.0 and coords.0 are specified. |
| y.0.var.hat | prediction variance if X.0 and coords.0 are specified. |
| run.time | execution time for building the nearest neighbor index and parameter estimation reported using proc.time(). |

The return object will include additional data used for subsequent prediction and/or model fit evaluation.

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References

Datta, A., S. Banerjee, A.O. Finley, and A.E. Gelfand. (2016) Hierarchical Nearest-Neighbor Gaussian process models for large geostatistical datasets. *Journal of the American Statistical Association*, 111:800-812.

Gneiting, T and A.E. Raftery. (2007) Strictly proper scoring rules, prediction, and estimation. *Journal of the American Statistical Association*, 102:359-378.

Examples

```
## Not run:
rmvn <- function(n, mu=0, V = matrix(1)){
  p <- length(mu)
  if(any(is.na(match(dim(V),p))))
    stop("Dimension problem!")
  D <- chol(V)
  t(matrix(rnorm(n*p), ncol=p)%*%D + rep(mu,rep(n,p)))
```

```

}

##Make some data
set.seed(1)
n <- 2000
coords <- cbind(runif(n,0,1), runif(n,0,1))

x <- cbind(1, rnorm(n))

B <- as.matrix(c(1,5))

sigma.sq <- 5
tau.sq <- 1
phi <- 3/0.5

D <- as.matrix(dist(coords))
R <- exp(-phi*D)
w <- rmvn(1, rep(0,n), sigma.sq*R)
y <- rnorm(n, x%*%B + w, sqrt(tau.sq))

ho <- sample(1:n, 1000)

y.ho <- y[ho]
x.ho <- x[ho,,drop=FALSE]
w.ho <- w[ho]
coords.ho <- coords[ho,]

y <- y[-ho]
x <- x[-ho,,drop=FALSE]
w <- w[-ho,,drop=FALSE]
coords <- coords[-ho,]

##Fit a Conjugate NNGP model and predict for the holdout
sigma.sq.IG <- c(2, sigma.sq)

cov.model <- "exponential"

g <- 10
theta.alpha <- cbind(seq(phi,30,length.out=g), seq(tau.sq/sigma.sq,5,length.out=g))

colnames(theta.alpha) <- c("phi", "alpha")

m.c <- spConjNNGP(y~x-1, coords=coords, n.neighbors = 10,
                  X.0 = x.ho, coords.0 = coords.ho,
                  k.fold = 5, score.rule = "crps",
                  n.omp.threads = 2,
                  theta.alpha = theta.alpha, sigma.sq.IG = sigma.sq.IG, cov.model = cov.model)

m.c$beta.hat
m.c$theta.alpha.sigmaSq
m.c$k.fold.scores

plot(m.c$y0.hat, y.ho)

```

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

spNNGP

Function for fitting univariate Bayesian spatial regression models

Description

The function `spNNGP` fits Gaussian univariate Bayesian spatial regression models using Nearest Neighbor Gaussian Processes (NNGP).

Usage

```
spNNGP(formula, data = parent.frame(), coords, method = "response", n.neighbors = 15,
        starting, tuning, priors, cov.model = "exponential",
        n.samples, n.omp.threads = 1, verbose=TRUE, n.report=100, ...)
```

Arguments

| | |
|--------------------------|---|
| <code>formula</code> | a symbolic description of the regression model to be fit. See example below. |
| <code>data</code> | an optional data frame containing the variables in the model. If not found in data, the variables are taken from <code>environment(formula)</code> , typically the environment from which <code>spNNGP</code> is called. |
| <code>coords</code> | an $n \times 2$ matrix of the observation coordinates in R^2 (e.g., easting and northing). |
| <code>method</code> | a quoted keyword that specifies the NNGP sampling algorithm. Supported method key words are: "response" and "sequential". See below for details. |
| <code>n.neighbors</code> | number of neighbors used in the NNGP. |
| <code>starting</code> | a list with each tag corresponding to a parameter name. Valid tags are <code>sigma.sq</code> , <code>tau.sq</code> , <code>phi</code> , and <code>nu</code> . <code>nu</code> needs to be specified if <code>cov.model="matern"</code> . The value portion of each tag is the parameter's starting value. |
| <code>tuning</code> | a list with each tag corresponding to a parameter name. Valid tags are <code>sigma.sq</code> , <code>tau.sq</code> , <code>phi</code> , and <code>nu</code> . If <code>method="sequential"</code> then only <code>phi</code> and <code>nu</code> need to be specified. The value portion of each tag defines the variance of the Metropolis sampler Normal proposal distribution. |
| <code>priors</code> | a list with each tag corresponding to a parameter name. Valid tags are <code>sigma.sq.ig</code> , <code>tau.sq.ig</code> , <code>phi.unif</code> . Variance parameters, <code>sigma.sq</code> and <code>tau.sq</code> , are assumed to follow an inverse-Gamma distribution, whereas the spatial decay <code>phi</code> and smoothness <code>nu</code> parameters are assumed to follow Uniform distributions. The hyperparameters of the inverse-Gamma are passed as a vector of length two, with the first and second elements corresponding to the <i>shape</i> and <i>scale</i> , respectively. The hyperparameters of the Uniform are also passed as a vector of length two with the first and second elements corresponding to the lower and upper support, respectively. |

| | |
|----------------------------|---|
| <code>cov.model</code> | a quoted keyword that specifies the covariance function used to model the spatial dependence structure among the observations. Supported covariance model key words are: "exponential", "matern", "spherical", and "gaussian". See below for details. |
| <code>n.samples</code> | the number of posterior samples to collect. |
| <code>n.omp.threads</code> | a positive integer indicating the number of threads to use for SMP parallel processing. The package must be compiled for OpenMP support. For most Intel-based machines, we recommend setting <code>n.omp.threads</code> to up to the number of hyperthreaded cores. |
| <code>verbose</code> | if TRUE, model specification and progress of the sampler is printed to the screen. Otherwise, nothing is printed to the screen. |
| <code>n.report</code> | the interval to report Metropolis sampler acceptance and MCMC progress. |
| <code>...</code> | currently no additional arguments. |

Details

Model parameters can be fixed at their starting values by setting their tuning values to zero.

The *no nugget* model is specified by setting `tau.sq` to zero in the starting and tuning lists.

Value

An object of class `rNNGP` or `sNNGP` depending on the method, which is a list comprising:

| | |
|------------------------------|---|
| <code>p.beta.samples</code> | a coda object of posterior samples for the regression coefficients. |
| <code>p.theta.samples</code> | a coda object of posterior samples for covariance parameters. |
| <code>run.time</code> | execution time for building the nearest neighbor index and MCMC sampler reported using <code>proc.time()</code> . |

The return object will include additional data used for subsequent prediction and/or model fit evaluation.

Author(s)

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 Sudipto Banerjee <sudipto@ucla.edu>

References

Datta, A., S. Banerjee, A.O. Finley, and A.E. Gelfand. (2016) Hierarchical Nearest-Neighbor Gaussian process models for large geostatistical datasets. *Journal of the American Statistical Association*, 111:800-812.

Examples

```
## Not run:

rmvn <- function(n, mu=0, V = matrix(1)){
  p <- length(mu)
  if(any(is.na(match(dim(V),p))))
    stop("Dimension problem!")
  D <- chol(V)
  t(matrix(rnorm(n*p), ncol=p)%*%D + rep(mu,rep(n,p)))
}

##Make some data
set.seed(1)
n <- 2000
coords <- cbind(runif(n,0,1), runif(n,0,1))

x <- cbind(1, rnorm(n))

B <- as.matrix(c(1,5))

sigma.sq <- 5
tau.sq <- 1
phi <- 3/0.5

D <- as.matrix(dist(coords))
R <- exp(-phi*D)
w <- rmvn(1, rep(0,n), sigma.sq*R)
y <- rnorm(n, x%*%B + w, sqrt(tau.sq))

ho <- sample(1:n, 1000)

y.ho <- y[ho]
x.ho <- x[ho,,drop=FALSE]
w.ho <- w[ho]
coords.ho <- coords[ho,]

y <- y[-ho]
x <- x[-ho,,drop=FALSE]
w <- w[-ho,,drop=FALSE]
coords <- coords[-ho,]

##Fit a Response and Sequential NNGP model
n.samples <- 1000

starting <- list("phi"=phi, "sigma.sq"=5, "tau.sq"=1)

tuning <- list("phi"=0.1, "sigma.sq"=0.1, "tau.sq"=0.1)

priors <- list("phi.Unif"=c(3/1, 3/0.01), "sigma.sq.IG"=c(2, 5), "tau.sq.IG"=c(2, 1))

cov.model <- "exponential"
```

```

n.report <- 500
verbose <- TRUE

m.s <- spNNGP(y~x-1, coords=coords, starting=starting, method="sequential", n.neighbors=10,
              tuning=tuning, priors=priors, cov.model=cov.model,
              n.samples=n.samples, n.omp.threads=2, verbose=verbose, n.report=n.report)

round(summary(m.s$sp.beta.samples)$quantiles[,c(3,1,5)],2)
round(summary(m.s$sp.theta.samples)$quantiles[,c(3,1,5)],2)

m.r <- spNNGP(y~x-1, coords=coords, starting=starting, method="response", n.neighbors=10,
              tuning=tuning, priors=priors, cov.model=cov.model,
              n.samples=n.samples, n.omp.threads=2, verbose=verbose, n.report=n.report)

round(summary(m.r$sp.beta.samples)$quantiles[,c(3,1,5)],2)
round(summary(m.r$sp.theta.samples)$quantiles[,c(3,1,5)],2)

## End(Not run)

```

spPredict

Function for prediction at new locations using spNNGP models.

Description

The function spPredict collects posterior predictive samples for a set of new locations given a [spNNGP](#) object.

Usage

```

spPredict(sp.obj, X.0, coords.0, start=1, end, thin=1,
          n.omp.threads = 1, verbose=TRUE, n.report=100, ...)

```

Arguments

| | |
|----------|--|
| sp.obj | an object returned by spNNGP . |
| X.0 | the design matrix for prediction locations. An intercept should be provided in the first column if one is specified in sp.obj model. |
| coords.0 | the spatial coordinates corresponding to X.0. |
| start | specifies the first sample included in the composition sampling. |
| end | specifies the last sample included in the composition. The default is to use all posterior samples in sp.obj. |
| thin | a sample thinning factor. The default of 1 considers all samples between start and end. For example, if thin = 10 then 1 in 10 samples are considered between start and end. |

| | |
|----------------------------|---|
| <code>n.omp.threads</code> | a positive integer indicating the number of threads to use for SMP parallel processing. The package must be compiled for OpenMP support. For most Intel-based machines, we recommend setting <code>n.omp.threads</code> to up to the number of hyperthreaded cores. |
| <code>verbose</code> | if TRUE, model specification and progress of the sampler is printed to the screen. Otherwise, nothing is printed to the screen. |
| <code>n.report</code> | the interval to report sampling progress. |
| <code>...</code> | currently no additional arguments. |

Value

A list comprising:

| | |
|-----------------------|--|
| <code>p.y.0</code> | a matrix that holds the response variable posterior predictive samples where rows are location corresponding to <code>coords.0</code> and columns are samples. |
| <code>p.w.0</code> | a matrix that holds the random effect posterior predictive samples where rows are location corresponding to <code>coords.0</code> and columns are samples. This is only returned if <code>spNNGP</code> method = "sequential". |
| <code>run.time</code> | execution time reported using <code>proc.time()</code> . |

The return object will include additional data used for subsequent prediction and/or model fit evaluation.

Author(s)

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 Abhirup Datta <abhidatta@jhu.edu>,
 Sudipto Banerjee <sudipto@ucla.edu>

References

Datta, A., S. Banerjee, A.O. Finley, and A.E. Gelfand. (2016) Hierarchical Nearest-Neighbor Gaussian process models for large geostatistical datasets. *Journal of the American Statistical Association*, 111:800-812.

Examples

```
## Not run:

rmvn <- function(n, mu=0, V = matrix(1)){
  p <- length(mu)
  if(any(is.na(match(dim(V),p))))
    stop("Dimension problem!")
  D <- chol(V)
  t(matrix(rnorm(n*p), ncol=p)%*%D + rep(mu,rep(n,p)))
}

##Make some data
set.seed(1)
n <- 2000
```

```

coords <- cbind(runif(n,0,1), runif(n,0,1))

x <- cbind(1, rnorm(n))

B <- as.matrix(c(1,5))

sigma.sq <- 5
tau.sq <- 1
phi <- 3/0.5

D <- as.matrix(dist(coords))
R <- exp(-phi*D)
w <- rmvn(1, rep(0,n), sigma.sq*R)
y <- rnorm(n, x%*%B + w, sqrt(tau.sq))

ho <- sample(1:n, 1000)

y.ho <- y[ho]
x.ho <- x[ho,,drop=FALSE]
w.ho <- w[ho]
coords.ho <- coords[ho,]

y <- y[-ho]
x <- x[-ho,,drop=FALSE]
w <- w[-ho,,drop=FALSE]
coords <- coords[-ho,]

##Fit a Response and Sequential NNGP model
n.samples <- 1000

starting <- list("phi"=phi, "sigma.sq"=5, "tau.sq"=1)

tuning <- list("phi"=0.1, "sigma.sq"=0.1, "tau.sq"=0.1)

priors <- list("phi.Unif"=c(3/1, 3/0.01), "sigma.sq.IG"=c(2, 5), "tau.sq.IG"=c(2, 1))

cov.model <- "exponential"

n.report <- 500
verbose <- TRUE

m.s <- spNNGP(y~x-1, coords=coords, starting=starting, method="sequential", n.neighbors=10,
             tuning=tuning, priors=priors, cov.model=cov.model,
             n.samples=n.samples, n.omp.threads=2, verbose=verbose, n.report=n.report)

round(summary(m.s$p.beta.samples)$quantiles[,c(3,1,5)],2)
round(summary(m.s$p.theta.samples)$quantiles[,c(3,1,5)],2)

m.r <- spNNGP(y~x-1, coords=coords, starting=starting, method="response", n.neighbors=10,
             tuning=tuning, priors=priors, cov.model=cov.model,
             n.samples=n.samples, n.omp.threads=2, verbose=verbose, n.report=n.report)

round(summary(m.r$p.beta.samples)$quantiles[,c(3,1,5)],2)

```

```
round(summary(m.r$p.theta.samples)$quantiles[,c(3,1,5)],2)

##Prediction for holdout data
p.s <- spPredict(m.s, X.0 = x.ho, coords.0 = coords.ho, n.omp.threads=2)

plot(apply(p.s$p.y.0, 1, mean), y.ho)
plot(apply(p.s$p.w.0, 1, mean), w.ho)

p.r <- spPredict(m.r, X.0 = x.ho, coords.0 = coords.ho, n.omp.threads=2)

plot(apply(p.r$p.y.0, 1, mean), y.ho)

## End(Not run)
```

Index

*Topic **model**

spConjNNGP, [1](#)

spNNGP, [5](#)

spPredict, [8](#)

spConjNNGP, [1](#)

spNNGP, [5](#), [8](#), [9](#)

spPredict, [8](#)