Package ‘ngspatial’

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    Linear Mixed Models for Areal Data
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    Gaussian areal data. The current version supports the sparse restricted
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R topics documented:

A ................................................................. 2
adjacency.matrix ............................................. 2
autologistic .................................................. 3
infant ........................................................... 7
negbinomial ................................................... 7
rautologistic ................................................. 8
residuals.autologistic ...................................... 9
Adjacency matrix for the infant mortality data.

A contains the adjacency matrix for the infant mortality data analyzed in (Hughes and Haran, 2013).

Usage

data(A)

Source

The data were obtained from the 2008 Area Resource File (ARF), a county-level database maintained by the Bureau of Health Professions, Health Resources and Services Administration, US Department of Health and Human Services.

Examples

data(A)

adjacency.matrix

Return an adjacency matrix for a square lattice.

Description

Return an adjacency matrix for a square lattice.

Usage

adjacency.matrix(m, n = NULL)

Arguments

m the number of rows in the lattice.

n the number of columns in the lattice. Defaults to NULL. If missing, the lattice is assumed to be m by m.
Details

This function builds the adjacency matrix for the $m$ by $n$ square lattice.

Value

A matrix $A$ of 0s and 1s, where $A_{ij}$ is equal to 1 iff vertices $i$ and $j$ are adjacent.

autologistic

Fit a centered autologistic model using maximum pseudolikelihood estimation or MCMC for Bayesian inference.

Description

Fit a centered autologistic model using maximum pseudolikelihood estimation or MCMC for Bayesian inference.

Usage

autologistic(formula, data, A, method = c("PL", "Bayes"), model = TRUE, x = FALSE, y = FALSE, verbose = FALSE, control = list())

Arguments

- **formula**: an object of class `formula`: a symbolic description of the model to be fitted.
- **data**: an optional data frame, list, or environment (or object coercible by `as.data.frame`) containing the variables in the model. If not found in `data`, the variables are taken from `environment(formula)`, typically the environment from which `autologistic` is called.
- **A**: the adjacency matrix for the underlying graph. The matrix need not be binary, but it must be numeric and symmetric.
- **method**: the method to use for inference. "PL" (the default) enables maximum pseudolikelihood estimation, and "Bayes" enables Bayesian inference.
- **model**: a logical value indicating whether the model frame should be included as a component of the returned value.
- **x**: a logical value indicating whether the model matrix used in the fitting process should be returned as a component of the returned value.
- **y**: a logical value indicating whether the response vector used in the fitting process should be returned as a component of the returned value.
- **verbose**: a logical value indicating whether to print various messages to the screen, including progress updates when method is "Bayes". Defaults to FALSE.
- **control**: a list of the following control parameters.
  - **confint (PL)**: the method for computing confidence intervals. The possible values are "sandwich" (the default), "bootstrap", and "none".
This function fits the centered autologistic model of Caragea and Kaiser (2009) using maximum pseudolikelihood estimation or MCMC for Bayesian inference. The joint distribution for the centered autologistic model is
\[
\pi(Z \mid \theta) = c(\theta)^{-1} \exp \left( Z' X \beta - \eta Z' A \mu + \frac{\eta}{2} Z' A Z \right),
\]
where \( \theta = (\beta', \eta)' \) is the parameter vector, \( c(\theta) \) is an intractable normalizing function, \( Z \) is the response vector, \( X \) is the design matrix, \( \beta \) is a \((p - 1)\)-vector of regression coefficients, \( A \) is the adjacency matrix for the underlying graph, \( \mu \) is the vector of independence expectations, and \( \eta \) is the spatial dependence parameter.

Maximum pseudolikelihood estimation sidesteps the intractability of \( c(\theta) \) by maximizing the product of the conditional likelihoods. Confidence intervals are then obtained using a parametric bootstrap or a normal approximation, i.e., sandwich estimation. The bootstrap datasets are generated by perfect sampling (\texttt{rautologistic}). The bootstrap samples can be generated in parallel using the \texttt{parallel} package.

Bayesian inference is obtained using the auxiliary variable algorithm of Moller et al. (2006). The auxiliary variables are generated by perfect sampling.

The prior distributions are (1) zero-mean normal with independent coordinates for \( \beta \), and (2) uniform for \( \eta \). The common standard deviation for the normal prior can be supplied by the user as control parameter \texttt{sigma}. The default is 1,000. The uniform prior has support \([0, 2]\) by default, but the right endpoint can be supplied (as control parameter \texttt{etaNmax}) by the user.

The posterior covariance matrix of \( \theta \) is estimated using samples obtained during a training run. The default number of iterations for the training run is 100,000, but this can be controlled by the user (via parameter \texttt{trainit}). The estimated covariance matrix is then used as the proposal variance for a Metropolis-Hastings random walk. The proposal distribution is normal. The posterior samples
obtained during the second run are used for inference. The length of the run can be controlled by the user via parameters minit, maxit, and tol. The first determines the minimum number of iterations. If minit has been reached, the sampler will terminate when maxit is reached or all Monte Carlo standard errors are smaller than tol, whichever happens first. The default values for minit, maxit, and tol are 100,000; 1,000,000; and 0.01, respectively.

Value

autologistic returns an object of class “autologistic”, which is a list containing the following components.

coefficients  the point estimate of $\theta$.
fitted.values  the fitted mean values, obtained by transforming the linear predictors by the inverse of the link function.
linear.predictors  the linear fit on link scale.
residuals  the response residuals.
iter  the size of the bootstrap/posterior sample.
sample  (where relevant) an iter by $p$ matrix containing the bootstrap/posterior samples.
mcese  (where relevant) a $p$-vector of Monte Carlo standard errors.
S  (where relevant) the estimated sandwich matrix.
accept  (Bayes) the acceptance rate for the MCMC sampler.
y  if requested (the default), the $y$ vector used.
X  if requested, the model matrix.
model  if requested (the default), the model frame.
call  the matched call.
formula  the formula supplied.
method  the method used for inference.
convergence  the integer code returned by optim subsequent to optimizing the pseudolikelihood.
message  a character string to go along with convergence.
terms  the terms object used.
data  the data argument.
xlevels  (where relevant) a record of the levels of the factors used in fitting.
control  a list containing the names and values of the control parameters.
value  the value of the negative log pseudolikelihood at its minimum.

References


See Also

`rautologistic`, `residuals.autologistic`, `summary.autologistic`, `vcov.autologistic`

Examples

```r
# Use the 20 x 20 square lattice as the underlying graph.

n = 20
A = adjacency.matrix(n)

# Assign coordinates to each vertex such that the coordinates are restricted to the unit square
# centered at the origin.

x = rep(0:(n - 1) / (n - 1), times = n) - 0.5
y = rep(0:(n - 1) / (n - 1), each = n) - 0.5
X = cbind(x, y)  # Use the vertex locations as spatial covariates.
beta = c(2, 2)  # These are the regression coefficients.
col1 = "white"
col2 = "black"
colfunc = colorRampPalette(c(col1, col2))

# Simulate a dataset with the above mentioned regression component and eta equal to 0.6. This
# value of eta corresponds to dependence that is moderate in strength.

theta = c(breaks, break2 = 0.6)
set.seed(123456)
Z = rautologistic(X, n, theta)

# Find the MLE, and do not compute confidence intervals.

fit = autologistic(Z ~ X - 1, A = A, control = list(confint = "none"))
summary(fit)

# The following examples are not executed by default since the computation is time consuming.

# Compute confidence intervals based on the normal approximation. Estimate the "filling" in the
# sandwich matrix using a parallel parametric bootstrap, where the computation is distributed
# across six cores on the host workstation.

# set.seed(123456)
# fit = autologistic(Z ~ X - 1, A = A, verbose = TRUE,
#                    control = list(confint = "sandwich", nodes = 6))
# summary(fit)

# Compute confidence intervals based on a parallel parametric bootstrap. Use a bootstrap sample
# of size 500, and distribute the computation across six cores on the host workstation.

# set.seed(123456)
# fit = autologistic(Z ~ X - 1, A = A, verbose = TRUE,
#                    control = list(confint = "bootstrap", bootit = 500, nodes = 6))
# summary(fit)
```
# Do MCMC for Bayesian inference. The length of the training run will be 10,000, and
# the length of the subsequent inferential run will be at least 10,000.

# set.seed(123456)
# fit = autologistic(Z ~ X - 1, A = A, verbose = TRUE, method = "Bayes",
#                   control = list(trainit = 10000, minit = 10000, sigma = 1000))
# summary(fit)

---

### infant

**Infant mortality data.**

**Description**

`infant` contains the infant mortality data analyzed in (Hughes and Haran, 2013).

**Usage**

```r
data(infant)
```

**Source**

The data were obtained from the 2008 Area Resource File (ARF), a county-level database maintained by the Bureau of Health Professions, Health Resources and Services Administration, US Department of Health and Human Services.

**Examples**

```r
data(infant)
```

---

### negbinomial

**Family function for negative binomial GLMs.**

**Description**

Provides the information required to apply a sparse SGLMM to conditionally negative binomial outcomes.

**Usage**

```r
negbinomial(theta = stop("'theta' must be specified."), link = "log")
```

**Arguments**

- **theta**: the dispersion parameter (must be positive).
- **link**: the link function, as a character string, name, or one-element character vector, specifying one of log, sqrt, or identity, or an object of class "link-glm"
Value
An object of class “family”, a list of functions and expressions needed to fit a negative binomial GLM.

rautologistic
Return a perfect sample from a centered autologistic model.

Description
Return a perfect sample from a centered autologistic model.

Usage
rautologistic(X, A, theta)

Arguments
X the design matrix.
A the adjacency matrix for the underlying graph. The matrix need not be binary, but it must be numeric and symmetric.
theta the vector of parameter values: θ = (β′, η)′.

Details
This function implements a perfect sampler for the centered autologistic model. The sampler employs coupling from the past.

Value
A vector that is distributed exactly according to the centered autologistic model with the given design matrix and parameter values.

References
Examples

```r
# Use the 20 x 20 square lattice as the underlying graph.

n = 20
A = adjacency.matrix(n)

# Assign coordinates to each vertex such that the coordinates are restricted to the unit square
# centered at the origin.

x = rep(0:(n - 1) / (n - 1), times = n) - 0.5
y = rep(0:(n - 1) / (n - 1), each = n) - 0.5
X = cbind(x, y)  # Use the vertex locations as spatial covariates.
beta = c(2, 2)  # These are the regression coefficients.

# Simulate a dataset with the above mentioned regression component and eta equal to 0.6. This
# value of eta corresponds to dependence that is moderate in strength.

theta = c(beta, eta = 0.6)
set.seed(123456)
Z = rautologistic(X, A, theta)
```

residuals.autologistic

*Extract model residuals.*

Description

Extract model residuals.

Usage

```r
## S3 method for class 'autologistic'
residuals(object, type = c("deviance", "pearson", "response"), ...)
```

Arguments

- `object`: an object of class autologistic, typically the result of a call to `autologistic`.
- `type`: the type of residuals that should be returned. The alternatives are “deviance” (default), “pearson”, and “response”.
- `...`: additional arguments.

Value

A vector of residuals.
See Also

autologistic, residuals.glm

residuals.sparse.sglm

Extract model residuals.

Description

Extract model residuals.

Usage

## S3 method for class 'sparse.sglm'
residuals(object, type = c("deviance", "pearson", "response"), ...)

Arguments

object an object of class sparse.sglm, typically the result of a call to sparse.sglm.

type the type of residuals that should be returned. The alternatives are "deviance" (default), "pearson", and "response".

... additional arguments.

Value

A vector of residuals.

See Also

sparse.sglm, residuals.glm

sparse.sglm

Fit a sparse SGLMM.

Description

Fit a sparse SGLMM.

Usage

sparse.sglm(formula, family = gaussian, data, offset, A, method = c("BSF", "RSR"), attractive = 50, repulsive = 0, tol = 0.01, minit = 10000, maxit = 1e+06, tune = list(), hyper = list(), model = TRUE, x = FALSE, y = FALSE, verbose = FALSE, parallel = FALSE)
sparse.sglmm

Arguments

formula an object of class formula: a symbolic description of the model to be fitted.

family a description of the error distribution and link function to be used in the model. This can be a character string naming a family function, a family function, or the result of a call to a family function. (See family for details of family functions.) Supported families are binomial, gaussian (default), negbinomial, and poisson.

data an optional data frame, list, or environment (or object coercible by as.data.frame to a data frame) containing the variables in the model. If not found in data, the variables are taken from environment(formula), typically the environment from which sparse.sglmm is called.

offset this can be used to specify an a priori known component to be included in the linear predictor during fitting. This should be NULL or a numeric vector of length equal to the number of cases. One or more offset terms can be included in the formula instead or as well, and if more than one is specified their sum is used. See model.offset.

A the adjacency matrix for the underlying graph.

method the basis to use. The options are Bayesian spatial filtering (“BSF”) and restricted spatial regression (“RSR”).

attractive the number of attractive Moran eigenvectors to use. The default is 50. See ‘Details’ for more information.

repulsive the number of repulsive Moran eigenvectors to use. The default is 0. See ‘Details’ for more information.

tol a tolerance. If all Monte Carlo standard errors are smaller than tol, no more samples are drawn from the posterior. The default is 0.01.

minit the minimum sample size. This should be large enough to permit accurate estimation of Monte Carlo standard errors. The default is 10,000.

maxit the maximum sample size. Sampling from the posterior terminates when all Monte Carlo standard errors are smaller than tol or when maxit samples have been drawn, whichever happens first. The default is 1,000,000.

tune (where relevant) a list containing sigma.s, sigma.h, and sigma.theta. These are the standard deviations for the $\gamma$, $\delta$, and $\theta$ proposals, respectively.

hyper a list containing sigma.b, the prior standard deviation for $\beta$, and (where relevant) a.h and b.h, the parameters of the gamma prior for $\tau_h$.

model a logical value indicating whether the model frame should be included as a component of the returned value.

x a logical value indicating whether the model matrix used in the fitting process should be returned as a component of the returned value.

y a logical value indicating whether the response vector used in the fitting process should be returned as a component of the returned value.

verbose a logical value indicating whether to print MCMC progress to the screen. Defaults to FALSE.
parallel (for parallelized computation of the Moran operator) a list containing type and nodes, the cluster type and number of slave nodes, respectively. The former must be one of “FORK”, “MPI”, “NWS”, “PSOCK”, or “SOCK” (default). The latter must be a whole number greater than 1. This argument defaults to FALSE, in which case the matrix multiplications are not parallelized.

Details

This function fits the sparse restricted spatial regression model of Hughes and Haran (2013), or the Bayesian spatial filtering model of Hughes (2017). The first stage of the model is

\[ g(\mu_i) = x_i' \beta + m_i' \gamma (i = 1, \ldots, n) \]

or, in vectorized form,

\[ g(\mu) = X \beta + M \gamma, \]

where \( X \) is the design matrix, \( \beta \) is a \( p \)-vector of regression coefficients, the columns of \( M \) are \( q \) eigenvectors of the Moran operator, and \( \gamma \) are spatial random effects. Arguments attractive and repulsive can be used to control the number of eigenvectors used. The default values are 50 and 0, respectively, which corresponds to pure spatial smoothing. Inclusion of some repulsive eigenvectors can be advantageous in certain applications.

The second stage, i.e., the prior for \( \gamma \), is

\[ p(\gamma | \tau_s) \propto \tau_s^{q/2} \exp \left( -\frac{\tau_s}{2} \gamma' M' Q M \gamma \right), \]

where \( \tau_s \) is a smoothing parameter and \( Q \) is the graph Laplacian.

The prior for \( \beta \) is spherical \( p \)-variate normal with mean zero and common standard deviation \( \text{sigmaNb} \), which defaults to 1,000. The prior for \( \tau_s \) is gamma with parameters 0.5 and 2,000. The same prior is used for \( \theta \) (when family is negbinomial).

When the response is normally distributed, the identity link is assumed, in which case the first stage is

\[ \mu = X \beta + M \gamma + M \delta, \]

where \( \delta \) are heterogeneity random effects. When the response is Poisson distributed, heterogeneity random effects are optional. In any case, the prior on \( \delta \) is spherical \( q \)-variate normal with mean zero and common variance \( 1/\tau_h \). The prior for \( \tau_h \) is gamma with parameters \( a_h \) and \( b_h \), the values of which are controlled by the user through argument hyper.

If the response is Bernoulli, negative binomial, or Poisson, \( \beta \) and \( \gamma \) are updated using Metropolis-Hastings random walks with normal proposals. The proposal covariance matrix for \( \beta \) is the estimated asymptotic covariance matrix from a \text{glm} fit to the data (see \text{vcov}). The proposal for \( \gamma \) is spherical normal with common standard deviation \( \text{sigmaNs} \).

The updates for \( \tau_s \) and \( \tau_h \) are Gibbs updates irrespective of the response distribution.

If the response is Poisson distributed and heterogeneity random effects are included, those random effects are updated using a Metropolis-Hastings random walk with a spherical normal proposal.
The common standard deviation is $\sigma_h$.

If the response is normally distributed, all updates are Gibbs updates.

If the response is negative binomial, the dispersion parameter $\theta$ is updated using a Metropolis-Hastings random walk with a normal proposal. Said proposal has standard deviation $\sigma_{\text{theta}}$, which can be provided by the user as an element of argument `tune`.

Value

`sparse.sglmm` returns an object of class "sparse.sglmm", which is a list containing the following components.

- `coefficients`: the estimated regression coefficients.
- `fitted.values`: the fitted mean values, obtained by transforming the linear predictors by the inverse of the link function.
- `linear.predictors`: the linear fit on link scale.
- `residuals`: the response residuals.
- `iter`: the size of the posterior sample.
- `beta.sample`: an iter by $p$ matrix containing the posterior samples for $\beta$.
- `gamma.sample`: an iter by $q$ matrix containing the posterior samples for $\gamma$.
- `delta.sample`: (where relevant) an iter by $q$ matrix containing the posterior samples for $\delta$.
- `theta.sample`: (where relevant) a vector containing the posterior samples for $\theta$.
- `tau.s.sample`: a vector containing the posterior samples for $\tau_s$.
- `tau.h.sample`: (where relevant) a vector containing the posterior samples for $\tau_h$.
- `gamma.est`: the estimate of $\gamma$.
- `delta.est`: (where relevant) the estimate of $\delta$.
- `tau.s.est`: the estimate of $\tau_s$.
- `tau.h.est`: (where relevant) the estimate of $\tau_h$.
- `theta.est`: (where relevant) the estimate of $\theta$.
- `beta.mcse`: the Monte Carlo standard errors for $\beta$.
- `gamma.mcse`: the Monte Carlo standard errors for $\gamma$.
- `delta.mcse`: (where relevant) the Monte Carlo standard errors for $\delta$.
- `tau.s.mcse`: the Monte Carlo standard error for $\tau_s$.
- `tau.h.mcse`: (where relevant) the Monte Carlo standard error for $\tau_h$.
- `theta.mcse`: (where relevant) the Monte Carlo standard error for $\theta$.
- `d.bar`: the goodness of fit component of the DIC.
- `pD`: the penalty component of the DIC.
- `dic`: the deviance information criterion.
- `beta.accept`: the acceptance rate for $\beta$. 


gamma.accept the acceptance rate for $\gamma$.
delta.accept (where relevant) the acceptance rate for $\delta$.
theta.accept (where relevant) the acceptance rate for $\theta$.
y if requested (the default), the y vector used.
X if requested, the model matrix.
M if requested, the matrix of Moran eigenvectors.
eigen.values if requested, the spectrum of the Moran operator.
hyper a list containing the names and values of the hyperparameters.
tune a list containing the names and values of the tuning parameters.
model if requested (the default), the model frame.
call the matched call.
formula the formula supplied.
terms the terms object used.
data the data argument.
offset the offset vector used.
xlevels (where relevant) a record of the levels of the factors used in fitting.

References


See Also

`residuals.sparse.sglmm`, `summary.sparse.sglmm`, `vcov.sparse.sglmm`

Examples

```r
## Not run:

The following code duplicates the analysis described in (Hughes and Haran, 2013). The data are infant mortality data for 3,071 US counties. We do a spatial Poisson regression with offset.

data(infant)
infant$low_weight = infant$low_weight / infant$births
attach(infant)
Z = deaths
X = cbind(1, low_weight, black, hispanic, gini, affluence, stability)
data(A)
set.seed(123456)
fit = sparse.sglmm(Z ~ X - 1 + offset(log(births)), family = poisson, A = A, method = "RSR",
                  tune = list(sigma.s = 0.02), verbose = TRUE)
summary(fit)

## End(Not run)
```
summary.autologistic

Print a summary of a centered autologistic model fit.

Description
Print a summary of a centered autologistic model fit.

Usage
## S3 method for class 'autologistic'
summary(object, alpha = 0.05, digits = 4, ...)

Arguments

object: an object of class autologistic, typically the result of a call to autologistic.
alpha: the significance level for the quantile/HPD intervals. The default is 0.05.
digits: the number of significant digits to display. The default is 4.
...: additional arguments.

Details
This function displays (1) the call to autologistic, (2) the values of the control parameters, (3) a table of estimates, and (4) the size of the bootstrap/posterior sample. Each row of the table of estimates shows a parameter estimate, the confidence or HPD interval for the parameter, and, where applicable, the Monte Carlo standard error.

See Also
autologistic

summary.sparse.sglm

Print a summary of a sparse SGLMM fit.

Description
Print a summary of a sparse SGLMM fit.

Usage
## S3 method for class 'sparse.sglm'
summary(object, alpha = 0.05, digits = 4, ...)


Arguments

object an object of class \texttt{sparse.sglmm}, typically the result of a call to \texttt{sparse.sglmm}.
alpha the significance level used to compute the HPD intervals. The default is 0.05.
digits the number of significant digits to display. The default is 4.
... additional arguments.

Details

This function displays (1) the call to \texttt{sparse.sglmm}, (2) the values of the hyperparameters and tuning parameters, (3) a table of estimates, (4) the DIC value for the fit, and (5) the number of posterior samples. Each row of the table of estimates shows an estimated regression coefficient, the HPD interval for the coefficient, and the Monte Carlo standard error.

See Also

\texttt{sparse.sglmm}

---

\texttt{vcov.autologistic} Return the estimated covariance matrix for an autologistic model object.

Description

Return the estimated covariance matrix for an autologistic model object.

Usage

```r
## S3 method for class 'autologistic'
vcov(object, ...)
```

Arguments

object a fitted autologistic model object.
... additional arguments.

Value

An estimate of the covariance matrix of the parameters (in a Bayesian setting), or an estimate of the covariance matrix of the maximum pseudolikelihood estimator of the parameters.
Return the covariance matrix of the regression parameters of a sparse.sglmm model object.

Usage

```r
## S3 method for class 'sparse.sglmm'
vcov(object, ...)
```

Arguments

- `object`: a fitted sparse.sglmm model object.
- `...`: additional arguments.

Value

An estimate of the posterior covariance matrix of the regression coefficients.
Index

+Topic datasets
  A, 2
  infant, 7

A, 2
adjacency.matrix, 2
as.data.frame, 3, 11
autologistic, 3, 9, 10, 15

family, 11
formula, 3, 11

glm, 12
infant, 7
model.offset, 11

negbinomial, 7

offset, 11
optim, 5

rautologistic, 4, 6, 8
residuals.autologistic, 6, 9
residuals.glm, 10
residuals.sparse.sglmm, 10, 14

sparse.sglmm, 10, 10, 16
summary.autologistic, 6, 15
summary.sparse.sglmm, 14, 15

terms, 5, 14

vcov, 12
vcov.autologistic, 6, 16
vcov.sparse.sglmm, 14, 17