

# Package ‘CDatanet’

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**Type** Package

**Title** Modeling Count Data with Peer Effects

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**Description**

Likelihood-based estimation and data generation from a class of models used to estimate peer effects on count data by controlling for the network endogeneity. This class includes count data models with social interactions (Houndetoungan 2020; <doi:10.2139/ssrn.3721250>), spatial tobit models (Xu and Lee 2015; <doi:10.1016/j.jeconom.2015.05.004>), and spatial linear-in-means models (Lee 2004; <doi:10.1111/j.1468-0262.2004.00558.x>).

**License** GPL-3

**Encoding** UTF-8

**BugReports** <https://github.com/ahoundetoungan/CDatanet/issues>

**URL** <https://github.com/ahoundetoungan/CDatanet>

**LazyData** true

**Depends** R (>= 3.5.0)

**Imports** Rcpp (>= 1.0.0), Formula, formula.tools, ddpcr, Matrix

**LinkingTo** Rcpp, RcppArmadillo, RcppProgress

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**Suggests** ggplot2, knitr, rmarkdown

**VignetteBuilder** knitr

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CDatanet-package	<i>The CDatanet package</i>
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## Description

The **CDatanet** package implements the count data model with social interactions and the dyadic linking model developed in Houndetoungan (2020). It also simulates data from the count data model and implements the Spatial Autoregressive Tobit model (LeSage, 2000; Xu and Lee, 2015) for left censored data and the Spatial Autoregressive Model (Lee, 2004). To make the computations faster **CDatanet** uses C++ through the **Rcpp** package (Eddelbuettel et al., 2011).

## Author(s)

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## References

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- Xu, X., & Lee, L. F., 2015, Maximum likelihood estimation of a spatial autoregressive Tobit model, *Journal of Econometrics*, 188(1), 264-280, doi: [10.1016/j.jeconom.2015.05.004](https://doi.org/10.1016/j.jeconom.2015.05.004)

**See Also**

[simCDnet](#), [CDnetNPL](#), [SARML](#), [SARTML](#) and [netformation](#).

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CDnetNPL	<i>Estimate Count Data Model with Social Interactions using NPL Method</i>
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**Description**

Estimate Count Data Model with Social Interactions using NPL Method

**Usage**

```
CDnetNPL(
  formula,
  contextual,
  Glist,
  theta0 = NULL,
  yb0 = NULL,
  optimizer = "optim",
  npl.ctr = list(),
  opt.ctr = list(),
  data
)
```

**Arguments**

formula	an object of class <a href="#">formula</a> : a symbolic description of the model. The formula should be as for example $y \sim x1 + x2 \mid x1 + x2$ where $y$ is the endogenous vector, the listed variables before the pipe, $x1$ , $x2$ are the individual exogenous variables and the listed variables after the pipe, $x1$ , $x2$ are the contextual observable variables. Other formulas may be $y \sim x1 + x2$ for the model without contextual effects, $y \sim -1 + x1 + x2 \mid x1 + x2$ for the model without intercept or $y \sim x1 + x2 \mid x2 + x3$ to allow the contextual variable to be different from the individual variables.
contextual	(optional) logical; if true, this means that all individual variables will be set as contextual variables. Set the the formula as $y \sim x1 + x2$ and contextual as TRUE is equivalent to set the formula as $y \sim x1 + x2 \mid x1 + x2$ .
Glist	the adjacency matrix or list sub-adjacency matrix.
theta0	(optional) starting value of $\theta = (\lambda, \beta, \gamma, \sigma)$ . The parameter $\gamma$ should be removed if the model does not contain contextual effects (see details).
yb0	(optional) expectation of $y$ .
optimizer	is either <code>nlm</code> (referring to the <a href="#">nlm</a> function) or <code>optim</code> (referring to the <a href="#">optim</a> function). At every step of the NPL method, the estimation is performed using <a href="#">nlm</a> or <a href="#">optim</a> . Other arguments of these functions such as, <code>control</code> and <code>method</code> can be defined through the argument <code>opt.ctr</code> .

<code>npl.ctr</code>	list of controls for the NPL method (see details).
<code>opt.ctr</code>	list of arguments of <code>nlm</code> or <code>optim</code> (the one set in optimizer) such as control, method, ...
<code>data</code>	an optional data frame, list or environment (or object coercible by <code>as.data.frame</code> to a 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 CDnetNPL is called.

## Details

### Model:

Following Houndetoungan (2020), the count data  $y$  is generated from a latent variable  $y^*$ . The latent variable is given for all  $i$  as

$$y_i^* = \lambda \mathbf{g}_i \bar{y} + \mathbf{x}_i' \beta + \mathbf{g}_i \mathbf{X} \gamma + \epsilon_i,$$

where  $\epsilon_i \sim N(0, \sigma^2)$ .

The count variable  $y_i$  is then define by the next (greater or equal) non negative integer to  $y_i^*$ ; that is  $y_i = 0$  if  $y_i^* \leq 0$  and  $y_i = q + 1$  if  $q < y_i^* \leq q + 1$ , where  $q$  is a non-negative integer.

### `npl.ctr`:

The model parameters is estimated using the Nested Partial Likelihood (NPL) method. This approach starts with a guess of  $\theta$  and  $\bar{y}$  and constructs iteratively a sequence of  $\theta$  and  $\bar{y}$ . The solution converges when the  $L_1$  distance between two consecutive  $\theta$  and  $\bar{y}$  is less than a tolerance. The argument `npl.ctr` is an optional list which contain

- tol the tolerance of the NPL algorithm (default 1e-4),
- maxit the maximal number of iterations allowed (default 500),
- print a boolean indicating if the estimate should be printed at each step.

### `codedata`:

The `class` of the output of this function is CDnetNPL. This class has a `summary` and `print methods` to summarize and print the results. The adjacency matrix and the data are needed to summarize the results. However, in order to save memory, the function does not return these objects. Instead, it returns `codedata` which contains among others, the `formula` and the names of these objects passed through the argument `Glist` and `data` (if provided). `codedata` will be used to get access to the adjacency matrix and the data. Therefore, it is important to have the adjacency matrix and the data (or the variables) available in `.GlobalEnv`. Otherwise, it will be necessary to provide them to the `summary` function.

## Value

A list consisting of:

<code>M</code>	number of sub-networks.
<code>n</code>	number of individuals in each network.
<code>iteration</code>	number of iterations performed by the NPL algorithm.
<code>estimate</code>	NPL estimator.

likelihood	pseudo-likelihood value.
yb	ybar (see details), expectation of y.
Gyb	average of the expectation of y among friends.
steps	step-by-step output as returned by the optimizer.
codedata	list of formula, name of the object Glist, number of friends in the network and name of the object data (see details).

### See Also

[simCDnet](#), [SARML](#) and [SARTML](#).

### Examples

```
# Groups' size
M      <- 5 # Number of sub-groups
nvec   <- round(runif(M, 100, 1000))
n      <- sum(nvec)

# Parameters
lambda <- 0.4
beta   <- c(2, -1.9, 0.8)
gamma  <- c(1.5, -1.2)
sigma  <- 1.5
theta  <- c(lambda, beta, gamma, sigma)

# X
X      <- cbind(rnorm(n, 1, 1), rexp(n, 0.4))

# Network
Glist  <- list()

for (m in 1:M) {
  nm    <- nvec[m]
  Gm    <- matrix(0, nm, nm)
  max_d <- 30
  for (i in 1:nm) {
    tmp  <- sample((1:nm)[-i], sample(0:max_d, 1))
    Gm[i, tmp] <- 1
  }
  rs    <- rowSums(Gm); rs[rs == 0] <- 1
  Gm    <- Gm/rs
  Glist[[m]] <- Gm
}

# data
data   <- data.frame(x1 = X[,1], x2 = X[,2])

rm(list = ls()[!(ls() %in% c("Glist", "data", "theta"))])
```

```

ytmp <- simCDnet(formula = ~ x1 + x2 | x1 + x2, Glist = Glist, theta = theta, data = data)

y <- ytmp$y

# plot histogram
hist(y, breaks = max(y))

data <- data.frame(yt = y, x1 = data$x1, x2 = data$x2)
rm(list = ls()[!(ls() %in% c("Glist", "data"))])

out <- CDnetNPL(formula = yt ~ x1 + x2, contextual = TRUE, Glist = Glist, data = data)
summary(out)

```

---

netformation

*Estimate Network Formation Model*


---

## Description

Estimate Network Formation Model

## Usage

```

netformation(
  network,
  formula,
  data,
  fixed.effects = TRUE,
  init = list(),
  mcmc.ctr = list(),
  print = TRUE
)

```

## Arguments

network	matrix or list of sub-matrix of social interactions containing 0 and 1, where links are represented by 1
formula	an object of class <a href="#">formula</a> : a symbolic description of the model. The formula should be as for example $\sim x1 + x2$ where $x1$ , $x2$ are explanatory variable of links formation
data	an optional data frame, list or environment (or object coercible by <a href="#">as.data.frame</a> 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 netformation is called.
fixed.effects	boolean indicating if sub-network heterogeneity as fixed effects should be included.

<code>init</code>	(optional) list of starting values containing <code>beta</code> , an $K$ -dimensional vector of the explanatory variables parameter, <code>mu</code> an $n$ -dimensional vector of unobserved parameters, <code>sigmau2</code> the vector of the variances of <code>mu</code> in each sub-network (or single variance if <code>fixed.effects = FALSE</code> ) and <code>uu</code> the vector of the means of <code>mu</code> in each sub-network (or single mean if <code>fixed.effects = FALSE</code> ), where $K$ is the number of explanatory variables and $n$ is the number of individuals.
<code>mcmc.ctr</code>	(optional) list of MCMC control (see detail).
<code>print</code>	boolean indicating if the estimation progression should be printed.

### Details

The network formation model can be used to control the network endogeneity in the count data, Tobit, and SAR models (see the vignette for an example with the count data model).

The MCMC control `mcmc.ctr` should be a list containing

- `jscalebeta` a  $K$ -dimensional vector of `beta` jumping scales.
- `jscalemu` an  $n$ -dimensional vector of `mu` jumping scales.
- `burnin` the number of iterations in the burn-in.
- `iteration` the number of simulations.
- `tbeta` target of `beta`.
- `tmu` target of `mu`.

The burn-in is replicated three times. The estimation is performed for each component of `beta` during the two firsts burn-in. The simulation from the second burn-in are used to compute covariance of `beta`. From the third burn-in and the remaining steps of the MCMC, all the components in `beta` are jointly simulated.

As `mu` dimension is large, the simulation is performed for each component.

The jumping scale are also updated during the MCMC following Atchadé and Rosenthal (2005).

### Value

A list consisting of:

<code>n</code>	number of individuals in each network.
<code>n.obs</code>	number of observations.
<code>n.links</code>	number of links.
<code>K</code>	number of explanatory variables.
<code>posterior</code>	list of simulations from the posterior distribution and the posterior density.
<code>acceptance.rate</code>	acceptance rate of <code>beta</code> and <code>mu</code> .
<code>mcmc.ctr</code>	returned list of MCMC control.
<code>init</code>	returned list of starting values.

**Examples**

```

M          <- 5 # Number of sub-groups
nvec       <- round(runif(M, 100, 500))
beta       <- c(1, -1)
Glist      <- list()
dX         <- matrix(0, 0, 2)
mu         <- list()
uu         <- runif(M, -5, 5)
sigma2u    <- runif(M, 0.5, 16)
for (m in 1:M) {
  n         <- nvec[m]
  mum       <- rnorm(n, uu[m], sqrt(sigma2u[m]))
  X1        <- rnorm(n)
  X2        <- rbinom(n, 1, 0.2)
  Z1        <- matrix(0, n, n)
  Z2        <- matrix(0, n, n)

  for (i in 1:n) {
    for (j in 1:n) {
      Z1[i, j] <- abs(X1[i] - X1[j])
      Z2[i, j] <- 1*(X2[i] == X2[j])
    }
  }

  Gm        <- 1*((Z1*beta[1] + Z2*beta[2] +
                 kronecker(mum, t(mum), "+") + rlogis(n^2)) > 0)
  diag(Gm)   <- 0

  diag(Z1)   <- NA
  diag(Z2)   <- NA
  Z1         <- Z1[!is.na(Z1)]
  Z2         <- Z2[!is.na(Z2)]

  dX         <- rbind(dX, cbind(Z1, Z2))
  Glist[[m]] <- Gm
  mu[[m]]    <- mum
}

mu <- unlist(mu)
out <- netformation(network = Glist, formula = ~ dX, fixed.effects = T,
                    mcmc.ctr = list(burin = 1000, iteration = 5000))

# plot simulations
plot(out$posterior$beta[,1], type = "l")
abline(h = beta[1], col = "red")
plot(out$posterior$beta[,2], type = "l")
abline(h = beta[2], col = "red")

k <- 2
plot(out$posterior$sigmamum2[,2], type = "l")

```



```

abline(h = sigma2u[2], col = "red")

i <- 10
plot(out$posterior$mu[,i], type = "l",
      ylim = c(min(out$posterior$mu[,i], mu[i]), max(out$posterior$mu[,i], mu[i])))
abline(h = mu[i], col = "red")

plot(out$posterior$uu[,k], type = "l",
      ylim = c(min(out$posterior$uu[,k], uu[k]), max(out$posterior$uu[,k], uu[k])))
abline(h = uu[k], col = "red")

```

SARML

*Estimate SAR model***Description**

Estimate SAR model

**Usage**

```

SARML(
  formula,
  contextual,
  Glist,
  lambda0 = NULL,
  optimizer = "optim",
  opt.ctr = list(),
  print = TRUE,
  cov = TRUE,
  data
)

```

**Arguments**

formula	an object of class <a href="#">formula</a> : a symbolic description of the model. The formula should be as for example $y \sim x_1 + x_2 \mid x_1 + x_2$ where $y$ is the endogenous vector, the listed variables before the pipe, $x_1, x_2$ are the individual exogenous variables and the listed variables after the pipe, $x_1, x_2$ are the contextual observable variables. Other formulas may be $y \sim x_1 + x_2$ for the model without contextual effects, $y \sim -1 + x_1 + x_2 \mid x_1 + x_2$ for the model without intercept or $y \sim x_1 + x_2 \mid x_2 + x_3$ to allow the contextual variable to be different from the individual variables.
contextual	(optional) logical; if true, this means that all individual variables will be set as contextual variables. Set the formula as $y \sim x_1 + x_2$ and contextual as TRUE is equivalent to set the formula as $y \sim x_1 + x_2 \mid x_1 + x_2$ .
Glist	the adjacency matrix or list sub-adjacency matrix.

<code>lambda0</code>	(optional) starting value of $\lambda$ . The parameter $\gamma$ should be removed if the model does not contain contextual effects (see details).
<code>optimizer</code>	is either <code>nlm</code> (referring to the function <a href="#">nlm</a> ) or <code>optim</code> (referring to the function <a href="#">optim</a> ). Other arguments of these functions such as, the control values and the method can be defined through the argument <code>opt.ctr</code> .
<code>opt.ctr</code>	list of arguments of <a href="#">nlm</a> or <a href="#">optim</a> (the one set in <code>optimizer</code> ) such as control, method, ...
<code>print</code>	a boolean indicating if the estimate should be printed at each step.
<code>cov</code>	a boolean indicating if the covariance should be computed.
<code>data</code>	an optional data frame, list or environment (or object coercible by <a href="#">as.data.frame</a> to a 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>mcmcARD</code> is called.

### Details

#### Model:

The variable  $y$  is given for all  $i$  as

$$y_i = \lambda \mathbf{g}_i' y + \mathbf{x}_i' \beta + \mathbf{g}_i \mathbf{X} \gamma + \epsilon_i,$$

where  $\epsilon_i \sim N(0, \sigma^2)$ .

#### codedata:

The [class](#) of the output of this function is `SAR`. This class has a [summary](#) and [print methods](#) to summarize and print the results. In order to save memory, the function does not return neither the adjacency matrix nor the data. Instead, it returns `codedata` which contains among others, the formula and the name of the adjacency matrix passed through the argument `Glist`.

### Value

A list consisting of:

<code>M</code>	number of sub-networks.
<code>n</code>	number of individuals in each network.
<code>estimate</code>	Maximum Likelihood (ML) estimator.
<code>likelihood</code>	likelihood value.
<code>cov</code>	covariance matrix of the estimate.
<code>optimization</code>	output as returned by the optimizer.
<code>codedata</code>	list of formula, name of the object <code>Glist</code> , number of friends in the network and name of the object data (see details).

### See Also

[CDnetNPL](#) and [SARTML](#).

**Examples**

```

# Groups' size
M      <- 5 # Number of sub-groups
nvec   <- round(runif(M, 100, 1000))
n      <- sum(nvec)

# Parameters
lambda <- 0.4
beta   <- c(2, -1.9, 0.8)
gamma  <- c(1.5, -1.2)
sigma  <- 1.5
theta  <- c(lambda, beta, gamma, sigma)

# X
X      <- cbind(rnorm(n, 1, 1), rexp(n, 0.4))

# Network
Glist  <- list()

for (m in 1:M) {
  nm    <- nvec[m]
  Gm    <- matrix(0, nm, nm)
  max_d <- 30
  for (i in 1:nm) {
    tmp  <- sample((1:nm)[-i], sample(0:max_d, 1))
    Gm[i, tmp] <- 1
  }
  rs    <- rowSums(Gm); rs[rs == 0] <- 1
  Gm    <- Gm/rs
  Glist[[m]] <- Gm
}

# data
data   <- data.frame(x1 = X[,1], x2 = X[,2])

rm(list = ls()[!(ls() %in% c("Glist", "data", "theta"))])

ytmp   <- simSARnet(formula = ~ x1 + x2 | x1 + x2, Glist = Glist,
                    theta = theta, data = data)

y      <- ytmp$y

# plot histogram
hist(y, breaks = max(y))

data   <- data.frame(yt = y, x1 = data$x1, x2 = data$x2)
rm(list = ls()[!(ls() %in% c("Glist", "data"))])

out    <- SARML(formula = yt ~ x1 + x2, contextual = TRUE,
                Glist = Glist, optimizer = "optim", data = data)

```

```
summary(out)
```

---

SARTML

*Estimate SART model*


---

## Description

Estimate SART model

## Usage

```
SARTML(
  formula,
  contextual,
  Glist,
  theta0 = NULL,
  optimizer = "optim",
  opt.ctr = list(),
  print = TRUE,
  cov = TRUE,
  data
)
```

## Arguments

formula	an object of class <a href="#">formula</a> : a symbolic description of the model. The formula should be as for example $y \sim x1 + x2 \mid x1 + x2$ where $y$ is the endogenous vector, the listed variables before the pipe, $x1, x2$ are the individual exogenous variables and the listed variables after the pipe, $x1, x2$ are the contextual observable variables. Other formulas may be $y \sim x1 + x2$ for the model without contextual effects, $y \sim -1 + x1 + x2 \mid x1 + x2$ for the model without intercept or $y \sim x1 + x2 \mid x2 + x3$ to allow the contextual variable to be different from the individual variables.
contextual	(optional) logical; if true, this means that all individual variables will be set as contextual variables. Set the formula as $y \sim x1 + x2$ and contextual as TRUE is equivalent to set the formula as $y \sim x1 + x2 \mid x1 + x2$ .
Glist	the adjacency matrix or list sub-adjacency matrix.
theta0	(optional) starting value of $\theta = (\lambda, \beta, \gamma, \sigma)$ . The parameter $\gamma$ should be removed if the model does not contain contextual effects (see details).
optimizer	is either <code>nlm</code> (referring to the function <a href="#">nlm</a> ) or <code>optim</code> (referring to the function <a href="#">optim</a> ). Other arguments of these functions such as, the control values and the method can be defined through the argument <code>opt.ctr</code> .
opt.ctr	list of arguments of <a href="#">nlm</a> or <a href="#">optim</a> (the one set in <code>optimizer</code> ) such as control, method, ...
print	a boolean indicating if the estimate should be printed at each step.

cov	a boolean indicating if the covariance should be computed.
data	an optional data frame, list or environment (or object coercible by <a href="#">as.data.frame</a> to a 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 SARTML is called.

## Details

### Model:

The left-censored variable  $y$  is generated from a latent variable  $y^*$ . The latent variable is given for all  $i$  as

$$y_i^* = \lambda \mathbf{g}_i y + \mathbf{x}_i' \beta + \mathbf{g}_i \mathbf{X} \gamma + \epsilon_i,$$

where  $\epsilon_i \sim N(0, \sigma^2)$ .

The count variable  $y_i$  is then define that is  $y_i = 0$  if  $y_i^* \leq 0$  and  $y_i = y_i^*$  otherwise.

### codedata:

The [class](#) of the output of this function is SARTML. This class has a [summary](#) and [print methods](#) to summarize and print the results. The adjacency matrix is needed to summarize the results. However, in order to save memory, the function does not return it. Instead, it returns `codedata` which contains the formula and the name of the adjacency matrix passed through the argument `Glist`. `codedata` will be used to get access to the adjacency matrix. Therefore, it is important to have the adjacency matrix available in `.GlobalEnv`. Otherwise it will be necessary to provide the adjacency matrix to the [summary](#) and [print](#) functions.

## Value

A list consisting of:

M	number of sub-networks.
n	number of individuals in each network.
estimate	Maximum Likelihood (ML) estimator.
likelihood	likelihood value.
cov	covariance matrix of the estimate.
optimization	output as returned by the optimizer.
codedata	list of formula, name of the object <code>Glist</code> , number of friends in the network, name of the object <code>data</code> , and number of zeros in <code>y</code> (see details).

## See Also

[CDnetNPL](#) and [SARML](#).

## Examples

```
# Groups' size
M <- 5 # Number of sub-groups
nvec <- round(runif(M, 100, 1000))
```

```

n      <- sum(nvec)

# Parameters
lambda <- 0.4
beta  <- c(2, -1.9, 0.8)
gamma <- c(1.5, -1.2)
sigma <- 1.5
theta <- c(lambda, beta, gamma, sigma)

# X
X      <- cbind(rnorm(n, 1, 1), rexp(n, 0.4))

# Network
Glist <- list()

for (m in 1:M) {
  nm      <- nvec[m]
  Gm      <- matrix(0, nm, nm)
  max_d   <- 30
  for (i in 1:nm) {
    tmp    <- sample((1:nm)[-i], sample(0:max_d, 1))
    Gm[i, tmp] <- 1
  }
  rs      <- rowSums(Gm); rs[rs == 0] <- 1
  Gm      <- Gm/rs
  Glist[[m]] <- Gm
}

# data
data <- data.frame(x1 = X[,1], x2 = X[,2])

rm(list = ls()[!(ls() %in% c("Glist", "data", "theta"))])

ytmp <- simTobitnet(formula = ~ x1 + x2 | x1 + x2, Glist = Glist,
                    theta = theta, data = data)

y      <- ytmp$y

# plot histogram
hist(y)

opt.ctr <- list(method = "Nelder-Mead",
                control = list(abstol = 1e-16, abstol = 1e-11, maxit = 5e3))
data <- data.frame(yt = y, x1 = data$x1, x2 = data$x2)
rm(list = ls()[!(ls() %in% c("Glist", "data"))])

out <- SARTML(formula = yt ~ x1 + x2, optimizer = "nlm",
              contextual = TRUE, Glist = Glist, data = data)
summary(out)

```

simCDnet

*Simulate data from Count Data Model with Social Interactions***Description**

Simulate data from Count Data Model with Social Interactions

**Usage**

```
simCDnet(formula, contextual, Glist, theta, tol = 1e-15, maxit = 500, data)
```

**Arguments**

formula	an object of class <a href="#">formula</a> : a symbolic description of the model. The formula should be as for example $y \sim x_1 + x_2 \mid x_1 + x_2$ where $y$ is the endogenous vector, the listed variables before the pipe, $x_1, x_2$ are the individual exogenous variables and the listed variables after the pipe, $x_1, x_2$ are the contextual observable variables. Other formulas may be $y \sim x_1 + x_2$ for the model without contextual effects, $y \sim -1 + x_1 + x_2 \mid x_1 + x_2$ for the model without intercept or $y \sim x_1 + x_2 \mid x_2 + x_3$ to allow the contextual variable to be different from the individual variables.
contextual	(optional) logical; if true, this means that all individual variables will be set as contextual variables. Set the formula as $y \sim x_1 + x_2$ and contextual as TRUE is equivalent to set the formula as $y \sim x_1 + x_2 \mid x_1 + x_2$ .
Glist	the adjacency matrix or list sub-adjacency matrix.
theta	the parameter value as $\theta = (\lambda, \beta, \gamma, \sigma)$ . The parameter $\gamma$ should be removed if the model does not contain contextual effects (see details).
tol	the tolerance value used in the Fixed Point Iteration Method to compute the expectancy of $y$ . The process stops if the $L_1$ distance between two consecutive values of the expectancy of $y$ is less than <code>tol</code> .
maxit	the maximal number of iterations in the Fixed Point Iteration Method.
data	an optional data frame, list or environment (or object coercible by <a href="#">as.data.frame</a> to a 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>mcmcARD</code> is called.

**Details**

Following Houndetoungan (2020), the count data  $y$  is generated from a latent variable  $\mathbf{y}^*$ . The latent variable is given for all  $i$  as

$$y_i^* = \lambda \mathbf{g}_i \bar{\mathbf{y}} + \mathbf{x}_i' \beta + \mathbf{g}_i \mathbf{X} \gamma + \epsilon_i,$$

where  $\epsilon_i \sim N(0, \sigma^2)$ .

The count variable  $y_i$  is then define by the next (greater or equal) non negative integer to  $y_i^*$ ; that is  $y_i = 0$  if  $y_i^* \leq 0$  and  $y_i = q + 1$  if  $q < y_i^* \leq q + 1$ , where  $q$  is a non-negative integer.

**Value**

A list consisting of:

yst	ys (see details), the latent variable.
y	the observed count data.
yb	ybar (see details), the expectation of y.
Gyb	the average of the expectation of y among friends.
iteration	number of iterations performed by sub-network in the Fixed Point Iteration Method.

**See Also**

[CDnetNPL](#).

**Examples**

```
# Groups' size
M      <- 5 # Number of sub-groups
nvec   <- round(runif(M, 100, 1000))
n      <- sum(nvec)

# Parameters
lambda <- 0.4
beta   <- c(2, -1.9, 0.8)
gamma  <- c(1.5, -1.2)
sigma  <- 1.5
theta  <- c(lambda, beta, gamma, sigma)

# X
X      <- cbind(rnorm(n, 1, 1), rexp(n, 0.4))

# Network
Glist  <- list()

for (m in 1:M) {
  nm    <- nvec[m]
  Gm    <- matrix(0, nm, nm)
  max_d <- 30
  for (i in 1:nm) {
    tmp  <- sample((1:nm)[-i], sample(0:max_d, 1))
    Gm[i, tmp] <- 1
  }
  rs    <- rowSums(Gm); rs[rs == 0] <- 1
  Gm    <- Gm/rs
  Glist[[m]] <- Gm
}

# data
data   <- data.frame(x1 = X[,1], x2 = X[,2])
```



```

rm(list = ls()[!(ls() %in% c("Glist", "data", "theta"))])

ytmp  <- simCDnet(formula = ~ x1 + x2 | x1 + x2, Glist = Glist,
                  theta = theta, data = data)

y      <- ytmp$y

# plot histogram
hist(y, breaks = max(y))

```

---

simSARnet

*Simulate data from the linear-in-mean Model with Social Interactions*


---

## Description

Simulate data from the linear-in-mean Model with Social Interactions

## Usage

```
simSARnet(formula, contextual, Glist, theta, data)
```

## Arguments

formula	an object of class <a href="#">formula</a> : a symbolic description of the model. The formula should be as for example $y \sim x1 + x2 \mid x1 + x2$ where $y$ is the endogenous vector, the listed variables before the pipe, $x1$ , $x2$ are the individual exogenous variables and the listed variables after the pipe, $x1$ , $x2$ are the contextual observable variables. Other formulas may be $y \sim x1 + x2$ for the model without contextual effects, $y \sim -1 + x1 + x2 \mid x1 + x2$ for the model without intercept or $y \sim x1 + x2 \mid x2 + x3$ to allow the contextual variable to be different from the individual variables.
contextual	(optional) logical; if true, this means that all individual variables will be set as contextual variables. Set the formula as $y \sim x1 + x2$ and contextual as TRUE is equivalent to set the formula as $y \sim x1 + x2 \mid x1 + x2$ .
Glist	the adjacency matrix or list sub-adjacency matrix.
theta	the parameter value as $\theta = (\lambda, \beta, \gamma, \sigma)$ . The parameter $\gamma$ should be removed if the model does not contain contextual effects (see details).
data	an optional data frame, list or environment (or object coercible by <a href="#">as.data.frame</a> to a 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>mcmcARD</code> is called.

**Details**

The variable  $y$  is given for all  $i$  as

$$y_i = \lambda \mathbf{g}_i y + \mathbf{x}_i' \beta + \mathbf{g}_i \mathbf{X} \gamma + \epsilon_i,$$

where  $\epsilon_i \sim N(0, \sigma^2)$ .

**Value**

A list consisting of:

$y$                     the observed count data.  
 $G_y$                   the average of  $y$  among friends.

**See Also**

[CDnetNPL](#).

**Examples**

```
# Groups' size
M      <- 5 # Number of sub-groups
nvec   <- round(runif(M, 100, 1000))
n      <- sum(nvec)

# Parameters
lambda <- 0.4
beta   <- c(2, -1.9, 0.8)
gamma  <- c(1.5, -1.2)
sigma  <- 1.5
theta  <- c(lambda, beta, gamma, sigma)

# X
X      <- cbind(rnorm(n, 1, 1), rexp(n, 0.4))

# Network
Glist  <- list()

for (m in 1:M) {
  nm    <- nvec[m]
  Gm    <- matrix(0, nm, nm)
  max_d <- 30
  for (i in 1:nm) {
    tmp  <- sample((1:nm)[-i], sample(0:max_d, 1))
    Gm[i, tmp] <- 1
  }
  rs    <- rowSums(Gm); rs[rs == 0] <- 1
  Gm    <- Gm/rs
  Glist[[m]] <- Gm
}
```

```

# data
data <- data.frame(x1 = X[,1], x2 = X[,2])

rm(list = ls()[!(ls() %in% c("Glist", "data", "theta"))])

ytmp <- simSARnet(formula = ~ x1 + x2 | x1 + x2, Glist = Glist,
                  theta = theta, data = data)
y <- ytmp$y

# plot histogram
hist(y)

```

simTobitnet

*Simulate data from the Tobit Model with Social Interactions***Description**

Simulate data from the Tobit Model with Social Interactions

**Usage**

```
simTobitnet(formula, contextual, Glist, theta, tol = 1e-15, maxit = 500, data)
```

**Arguments**

formula	an object of class <a href="#">formula</a> : a symbolic description of the model. The formula should be as for example $y \sim x_1 + x_2 \mid x_1 + x_2$ where $y$ is the endogenous vector, the listed variables before the pipe, $x_1, x_2$ are the individual exogenous variables and the listed variables after the pipe, $x_1, x_2$ are the contextual observable variables. Other formulas may be $y \sim x_1 + x_2$ for the model without contextual effects, $y \sim -1 + x_1 + x_2 \mid x_1 + x_2$ for the model without intercept or $y \sim x_1 + x_2 \mid x_2 + x_3$ to allow the contextual variable to be different from the individual variables.
contextual	(optional) logical; if true, this means that all individual variables will be set as contextual variables. Set the formula as $y \sim x_1 + x_2$ and contextual as TRUE is equivalent to set the formula as $y \sim x_1 + x_2 \mid x_1 + x_2$ .
Glist	the adjacency matrix or list sub-adjacency matrix.
theta	the parameter value as $\theta = (\lambda, \beta, \gamma, \sigma)$ . The parameter $\gamma$ should be removed if the model does not contain contextual effects (see details).
tol	the tolerance value used in the Fixed Point Iteration Method to compute $y$ . The process stops if the $L_1$ distance between two consecutive values of $y$ is less than <code>tol</code> .
maxit	the maximal number of iterations in the Fixed Point Iteration Method.
data	an optional data frame, list or environment (or object coercible by <a href="#">as.data.frame</a> to a 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>mcmcARD</code> is called.

## Details

The left-censored variable  $y$  is generated from a latent variable  $y^*$ . The latent variable is given for all  $i$  as

$$y_i^* = \lambda \mathbf{g}_i y + \mathbf{x}_i' \beta + \mathbf{g}_i \mathbf{X} \gamma + \epsilon_i,$$

where  $\epsilon_i \sim N(0, \sigma^2)$ .

The count variable  $y_i$  is then define that is  $y_i = 0$  if  $y_i^* \leq 0$  and  $y_i = y_i^*$  otherwise.

## Value

A list consisting of:

yst	ys (see details), the latent variable.
y	the observed count data.
Gy	the average of y among friends.
iteration	number of iterations performed by sub-network in the Fixed Point Iteration Method.

## See Also

[CDnetNPL](#).

## Examples

```
# Groups' size
M      <- 5 # Number of sub-groups
nvec   <- round(runif(M, 100, 1000))
n      <- sum(nvec)

# Parameters
lambda <- 0.4
beta   <- c(2, -1.9, 0.8)
gamma  <- c(1.5, -1.2)
sigma  <- 1.5
theta  <- c(lambda, beta, gamma, sigma)

# X
X      <- cbind(rnorm(n, 1, 1), rexp(n, 0.4))

# Network
Glist  <- list()

for (m in 1:M) {
  nm    <- nvec[m]
  Gm    <- matrix(0, nm, nm)
  max_d <- 30
  for (i in 1:nm) {
    tmp  <- sample((1:nm)[-i], sample(0:max_d, 1))
    Gm[i, tmp] <- 1
  }
  rs    <- rowSums(Gm); rs[rs == 0] <- 1
}
```

```

    Gm          <- Gm/rs
    Glist[[m]]  <- Gm
  }

# data
data <- data.frame(x1 = X[,1], x2 = X[,2])

rm(list = ls()[!(ls() %in% c("Glist", "data", "theta"))])

ytmp <- simTobitnet(formula = ~ x1 + x2 | x1 + x2, Glist = Glist,
                    theta = theta, data = data)

y <- ytmp$y

# plot histogram
hist(y)

```

summary.CDnetNPL

*Summarize Count Data Model with Social Interactions***Description**

Summary and print methods for the class CDnetNPL as returned by the function [CDnetNPL](#).

**Usage**

```

## S3 method for class 'CDnetNPL'
summary(object, cov.ctr = list(), Glist, data, ...)

## S3 method for class 'summary.CDnetNPL'
print(x, ...)

## S3 method for class 'CDnetNPL'
print(x, ...)

## S3 method for class 'summary.CDnetNPLs'
print(x, ...)

```

**Arguments**

object	an object of class CDnetNPL, output of the function <a href="#">CDnetNPL</a> .
cov.ctr	list of control values for the covariance containing two integers, R and S. The covariance summations from 0 to infinity. But the summed elements decreases exponentially. The summations are approximated by summations from 0 to R. The covariance also requires computing $\Phi(x) - \Phi(x-1)$ , where $\Phi$ is the normal probability density function. This is done using important sampling, where S numbers are generated from the uniform distribution.

<code>Glist</code>	the adjacency matrix or list sub-adjacency matrix. If missing make, sure that the object provided to the function <code>CDnetNPL</code> is available in <code>.GlobalEnv</code> (see detail - <code>codedata</code> section of <code>CDnetNPL</code> ).
<code>data</code>	dataframe containing the explanatory variables. If missing make, sure that the object provided to the function <code>CDnetNPL</code> is available in <code>.GlobalEnv</code> (see detail - <code>codedata</code> section of <code>CDnetNPL</code> ).
<code>...</code>	further arguments passed to or from other methods.
<code>x</code>	an object of class <code>summary.CDnetNPL</code> , output of the function <code>summary.CDnetNPL</code> , class <code>summary.CDnetNPLs</code> , list of outputs of the function <code>summary.CDnetNPL</code> (when the model is estimated many times to control for the endogeneity) or class <code>CDnetNPL</code> of the function <code>CDnetNPL</code> .

### Value

A list consisting of:

<code>M</code>	number of sub-networks.
<code>n</code>	number of individuals in each network.
<code>iteration</code>	number of iterations performed by the NPL algorithm.
<code>estimate</code>	NPL estimator.
<code>likelihood</code>	pseudo-likelihood value.
<code>yb</code>	$\bar{y}$ (see details), expectation of $y$ .
<code>Gyb</code>	average of the expectation of $y$ among friends.
<code>steps</code>	step-by-step output as returned by the optimizer.
<code>cov</code>	covariance matrix of the estimate.
<code>meffects</code>	vector of marginal effects.
<code>cov.me</code>	covariance matrix of the marginal effects.
<code>cov.ctr</code>	returned value of the control values for the covariance.
<code>codedata</code>	list of formula, name of the object <code>Glist</code> , number of friends in the network and name of the object <code>data</code> .

---

summary.SARML

*Summarize SAR Model*

---

### Description

Summary and print methods for the class `SARML` as returned by the function `SARML`.

**Usage**

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

## S3 method for class 'summary.SARML'
print(x, ...)

## S3 method for class 'SARML'
print(x, ...)

## S3 method for class 'summary.SARMLs'
print(x, ...)
```

**Arguments**

object	an object of class SARML, output of the function <a href="#">SARML</a> .
...	further arguments passed to or from other methods.
x	an object of class summary.SARML, output of the function <a href="#">summary.SARML</a> or class SARML, output of the function <a href="#">SARML</a> .

**Value**

A list consisting of:

M	number of sub-networks.
n	number of individuals in each network.
estimate	Maximum Likelihood (ML) estimator.
likelihood	likelihood value.
cov	covariance matrix of the estimate.
optimization	output as returned by the optimizer.
codedata	list of formula, name of the object Glist, number of friends in the network and name of the object data.

---

summary.SARTML

*Summarize SART Model*


---

**Description**

Summary and print methods for the class SARTML as returned by the function [SARTML](#).

**Usage**

```
## S3 method for class 'SARTML'
summary(object, Glist, data, ...)

## S3 method for class 'summary.SARTML'
print(x, ...)

## S3 method for class 'SARTML'
print(x, ...)

## S3 method for class 'summary.SARTMLs'
print(x, ...)
```

**Arguments**

object	an object of class SARTML, output of the function <a href="#">SARTML</a> .
Glist	the adjacency matrix or list sub-adjacency matrix. If missing make, sure that the object provided to the function <a href="#">SARTML</a> is available in .GlobalEnv (see detail - codedata section of <a href="#">SARTML</a> ).
data	dataframe containing the explanatory variables. If missing make, sure that the object provided to the function <a href="#">SARTML</a> is available in .GlobalEnv (see detail - codedata section of <a href="#">SARTML</a> ).
...	further arguments passed to or from other methods.
x	an object of class summary.SARTML, output of the function <a href="#">summary.SARTML</a> or class SARTML, output of the function <a href="#">SARTML</a> .

**Value**

A list consisting of:

M	number of sub-networks.
n	number of individuals in each network.
estimate	Maximum Likelihood (ML) estimator.
likelihood	likelihood value.
cov	covariance matrix of the estimate.
optimization	output as returned by the optimizer.
codedata	list of formula, name of the object Glist, number of friends in the network, name of the object data, and number of zeros in y.



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