

# CDatanet: An R package to simulate and estimate a Count Data Model with Social Interactions

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## 1 Introduction

There is a large and growing literature on peer effects in economics.<sup>1</sup> Recent contributions include among other, models for discrete data such as binary (e.g., Lee et al., 2014; Liu, 2019), ordered (e.g., Boucher et al., 2018) and multinomial (e.g., Guerra and Mohnen, 2017). However, there are hardly any models dealing with count data (e.g., data collected by asking respondents: “How many times do you smoke daily?”).

I present a model in which the outcome takes count values (0, 1, 2, ...). In this model, individuals interact through a directed network and their peers’ decision may influence their own decision. Moreover, they do not observe their peers’ outcome and form rational belief about that.

I also present an easy-to-use R package—named **CDatanet**—for implementing the model. This note is a supplement for the package manual. I provide examples with simulated data to show how to use the package. The package is located on GitHub at [github.com/ahoundetoungan/CDatanet](https://github.com/ahoundetoungan/CDatanet). All the results of the note can be replicated following the code provided.

The rest of this note is organized as follow. Section 2 briefly introduces the model. Section 3 explains how to install the package. Sections 4 and 5 provide examples in which the network matrix is assumed exogenous and endogenous respectively. They present Monte Carlo experiments to assess the performance of the estimator of the model parameters. They also discuss how to control for the endogeneity of the network. Section 6 concludes.

## 2 Model

Let  $\mathcal{V} = \{1, \dots, n\}$  be a set of  $n$  players indexed by  $i$  and  $y_i$  the observed integer outcome of player  $i$  (e.g., the number of cigarettes smoked per day or per week). I denote by  $\mathbf{G}$  the adjacency matrix such that  $G_{ij} = \frac{1}{n_i}$  if  $i$  knows  $j$  and  $G_{ij} = 0$  otherwise, where  $n_i$  the number of friends of  $i$ . Let also  $\mathbf{X}$  be the matrix of explanatory variables.

As in Liu (2019), I assume that there is a latent variable  $y_i^*$  which determines the observed count variable  $y_i$ . This latent variable  $y_i^*$  and the observed  $y_i$  are linked as follow.

Let be  $(a_q)_{q \in \mathbb{N}}$  a sequence given by  $a_0 = -\infty$ ,  $a_1 \in \mathbb{R}$  and  $a_q = a_1 + \gamma(q - 1)$  for  $q \in \mathbb{N}^*$  and  $\gamma \in \mathbb{R}_+^*$ . If  $y_i^* \in (a_q, a_{q+1}]$  then  $y_i = q$ .

The first order conditions of the game equilibrium implies that

$$y_i^* = \lambda \sum_{i=1}^n \sum_{r=0}^{\infty} r G_{ij} p_{ir} + \mathbf{x}_i' \boldsymbol{\beta} + \varepsilon_i$$

---

<sup>1</sup>For recent reviews, see Boucher and Fortin (2016), De Paula (2017) and Bramoullé et al. (2019).

where  $p_{ir}$  is the probability of  $y_i = r$ ,  $\lambda$  is the peer effect and  $\varepsilon_i \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ .

The game equilibrium is given by

$$p_{ir} = \Phi \left( \frac{\lambda \sum_{i=1}^n \sum_{r=0}^{\infty} r G_{ij} p_{ir} + \mathbf{x}'_i \boldsymbol{\beta} - a_q}{\sigma_\varepsilon} \right) - \Phi \left( \frac{\lambda \sum_{i=1}^n \sum_{r=0}^{\infty} r G_{ij} p_{ir} + \mathbf{x}'_i \boldsymbol{\beta} - a_{q+1}}{\sigma_\varepsilon} \right)$$

where  $\Phi$  is the probability density function of  $\mathcal{N}(0, 1)$ .

To estimate  $\boldsymbol{\theta} = (\lambda, \boldsymbol{\beta}', \sigma_\varepsilon)'$ , I rely on the NPL method. I refer the reader to [Houndetoungan \(2020\)](#) for more details. The estimation method is implemented in the package **CDatanet**.

### 3 CDatanet Installation

The code source of the package is written in C++ with the package **Rcpp** ([Eddelbuettel et al., 2020](#)). **CDatanet** is currently available on GitHub. Its installation requires to prior install **devtools** package ([Wickham et al., 2020](#)). Moreover, Windows users should install Rtools compatible with their R version.

**CDatanet** package can be installed from this GitHub repos using the `install_github` function of **devtools**. All the dependencies will also be installed automatically.

```
library(devtools)
install_github("ahoundetoungan/CDatanet")
```

## 4 Examples with exogenous network

In this section, I present examples to show how to use the package. I simulate data following the model by assuming that the network matrix is exogenous. I then show how to estimate the model parameters using functions implemented in **CDatanet**. I also use Monte Carlo simulations to assess the performance of the estimator of the model parameters.

### 4.1 Data simulation

Given the adjacency matrix, the explanatory variables and  $\boldsymbol{\theta}$ , the function `simCDnet` can be used to simulate data. I assume that there are  $M$  sub-networks. The number of individuals in each sub-network is randomly chosen between 100 and 1000. I assume two exogenous variables (plus the intercept) and I control for the contextual effect.

```
set.seed(2020)
library(CDatanet)
# Groups' size
M      <- 5 # Number of sub-groups
nvec   <- round(runif(M, 100, 1000))
print(nvec)

## [1] 682 455 657 529 222

n      <- sum(nvec)
print(n)

## [1] 2545

# Parameters
lambda <- 0.4          # peer effect
beta   <- c(2, -1.9, 0.8) # own effects
gamma  <- c(1.5, -1.2)   # contextual effects
sigma  <- 1.5           # standard deviation of epsilon
```

```
theta <- c(lambda, beta, gamma, sigma)

# X
data <- data.frame(x1 = rnorm(n, 1, 1), x2 = rexp(n, 0.4))
```

To simulate the network matrix, I assume that the number of friends of each individual is randomly chosen between 0 and 30.

```
# 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
}
```

I can now simulate the count data. The output of `simCDnet` includes `yst` the vector of  $y_i^*$ , `y` the vector of  $y_i$ , `yb` the vector of  $\sum_{r=0}^{\infty} r p_{ir}$ , `Gyb` the vector of  $\sum_{i=1}^n \sum_{r=0}^{\infty} r G_{ij} p_{ir}$  and `iteration` as the number of iterations performed to find the fixed point `yb`.

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

```
## [1] "yst"      "y"        "yb"       "Gyb"      "iteration"
```

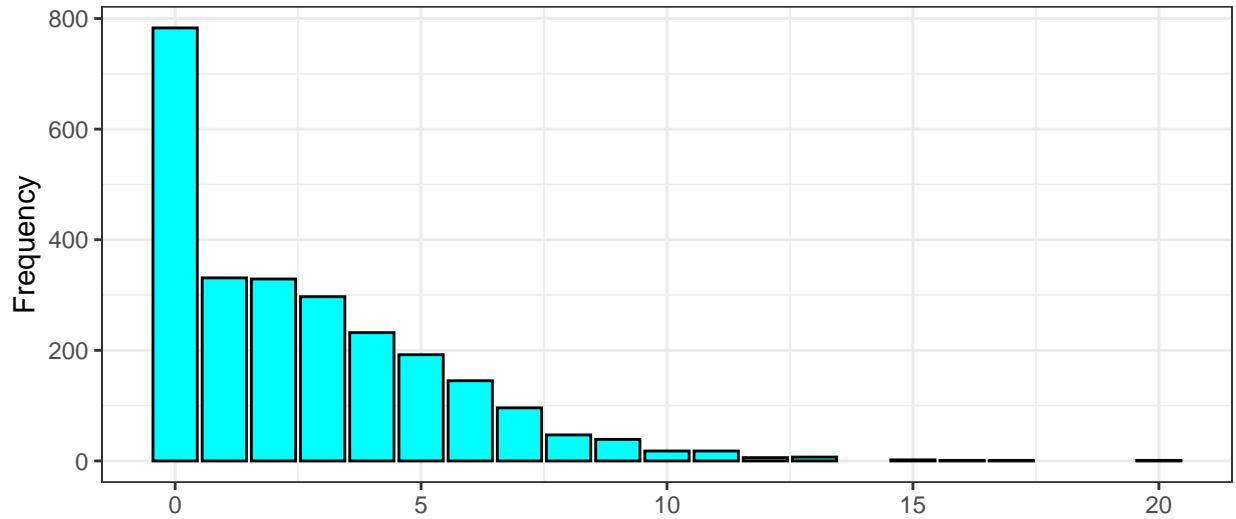
```
y <- ytmp$y
# Add y to data
data$y <- y
# Summarize y
summary(y)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.000   0.000   2.000   2.617   4.000   20.000
```

```
table(y)
```

```
## y
##  0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20
## 783 331 329 297 232 192 145 96 47 39 18 18 6 7 2 1 1 1 1 1
```

```
# Plot data histogram
library(ggplot2)
print(ggplot(data = data.frame(y = y), aes(x = y)) +
  geom_bar(color = "black", fill = "cyan") +
  theme_bw() + xlab("") + ylab("Frequency"))
```



## 4.2 Estimation

Using the simulated data, I estimate the count data model as well as the SART and SAR models. The output of these models has a `summary` class to summarize the results. In addition, the `summary` function computes marginal effects for the count data model.

```
# Count data
CD <- CDnetNPL(formula = y ~ x1 + x2, contextual = TRUE, Glist = Glist,
               optimizer = "nlm",
               data = data, npl.ctr = list(print = FALSE, maxit = 5e3))
summary(CD)
```

```
## Count data Model with Social Interactions
##
## Method: Nested pseudo-likelihood (NPL)
## Iteration: 12
##
## Network:
## Number of groups      : 5
## Sample size          : 2545
## Average number of friends: 14.98075
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## lambda      0.377313   0.075603   4.99 6.02e-07 ***
## (Intercept) 1.940142   0.155886  12.45 <2e-16 ***
## x1          -1.836252   0.037055 -49.55 <2e-16 ***
## x2           0.804280   0.012901  62.34 <2e-16 ***
## G: x1        1.587260   0.112376  14.12 <2e-16 ***
## G: x2       -1.211202   0.074873 -16.18 <2e-16 ***
##
## Marginal Effects:
##              Estimate Std. Error t value Pr(>|t|)
## lambda      0.283665   0.056942   4.98 6.31e-07 ***
## (Intercept) 1.458607   0.117014  12.47 <2e-16 ***
## x1          -1.380502   0.033611 -41.07 <2e-16 ***
## x2           0.604661   0.011963  50.55 <2e-16 ***
## G: x1        1.193309   0.086218  13.84 <2e-16 ***
```

```

## G: x2      -0.910587   0.057630  -15.80   <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## sigma: 1.503368
## log pseudo-likelihood: -3650.167

# SART
SART <- SARTML(formula = y ~ x1 + x2, contextual = TRUE, Glist = Glist,
               optimizer = "nlm", data = data, print = FALSE)
summary(SART)

## SART Model
##
## Method: Maximum Likelihood (ML)
##
## Network:
## Number of groups      : 5
## Sample size           : 2545
## Average number of friends: 14.98075
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## lambda      0.266098   0.056614   4.70 2.6e-06 ***
## (Intercept) 2.526843   0.150888  16.75 <2e-16 ***
## x1          -1.929519   0.039198 -49.23 <2e-16 ***
## x2           0.829310   0.013658  60.72 <2e-16 ***
## G: x1        1.539243   0.110878  13.88 <2e-16 ***
## G: x2       -1.157105   0.063618 -18.19 <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## sigma: 1.630561
## log likelihood: -3811.928

# SAR
SAR <- SARML(formula = y ~ x1 + x2, contextual = TRUE, Glist = Glist,
              optimizer = "nlm", data = data, print = FALSE)
summary(SAR)

## SAR Model
##
## Method: Maximum Likelihood (ML)
##
## Network:
## Number of groups      : 5
## Sample size           : 2545
## Average number of friends: 14.98075
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## lambda      0.163839   0.043641   3.75 0.000174 ***
## (Intercept) 2.532121   0.117490  21.55 <2e-16 ***
## x1          -1.386272   0.027828 -49.82 <2e-16 ***
## x2           0.706970   0.010947  64.58 <2e-16 ***
## G: x1        1.084204   0.085506  12.68 <2e-16 ***

```

```
## G: x2      -0.738526   0.046377  -15.92   <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## sigma: 1.382775
## log likelihood: -4436.1
```

Using the count data model, the peer effect is estimated at 0.38, which is close to the true value, 0.4. By replicating this experience several times, the average of the estimates is likely to be almost equal to the true value (see next section). Note that this parameter is not interpretable. Instead, one should interpret the marginal effect: *increasing of the expected  $y_j$  of the peers by one implies an increasing of the expected  $y_i$  of the individual by 0.28*. However, estimating the SART model using data simulated from the count data model underestimates the peer effect (0.27). The package does not implement the marginal effect under the SART model. This latter should be much lower. Lastly, the SAR model more underestimates the peer effect (0.16). In addition, this is directly the marginal effect because the SAR model does not assume a limited dependent variable.

### 4.3 Monte Carlo Simulations

In this section, I conduct Monte Carlo simulations to assess the performance of the estimator. I use the same settings as in Section 4.1 except that the number of individuals in each sub-network is set to 500. Let's build the following Monte Carlo function that simulates the data, estimates the three models and returns their estimators.

```
fMC <- function(s) {
  # Groups' size
  M      <- 5
  nvec   <- rep(500, 5);
  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
  data   <- data.frame(x1 = rnorm(n, 1, 1), x2 = 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
  }

  # y
```

```

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

# Models
CD       <- CDnetNPL(formula = y ~ x1 + x2, contextual = TRUE, Glist = Glist,
                    optimizer = "nlm",
                    data = data, npl.ctr = list(print = FALSE, maxit = 5e3))
SART     <- SARTML(formula = y ~ x1 + x2, contextual = TRUE, Glist = Glist,
                    optimizer = "nlm", data = data, print = FALSE)
SAR      <- SARML(formula = y ~ x1 + x2, contextual = TRUE, Glist = Glist,
                    optimizer = "nlm", data = data, print = FALSE)
c(CD$estimate, SART$estimate, SAR$estimate)
}

```

I run the Monte Carlo function `fMC` 1000 times and compute the average of each estimator. To make it faster, I run the replications in parallel using `doParallel` package (Corporation and Weston, 2019).

```

library(doParallel)
n.cores <- 32
replic  <- 1000 #Number of replications
out.mc  <- mclapply(1:replic, fMC, mc.cores = n.cores)
out.mc  <- apply(t(do.call(cbind, out.mc)), 2, mean)
out.mc  <- cbind(theta, out.mc[1:7], out.mc[8:14], out.mc[15:21])
colnames(out.mc) <- c("TrueValue", "CoutData", "SART", "SAR")
print(out.mc)

```

##	TrueValue	CoutData	SART	SAR
## lambda	0.4	0.4014868	0.2073720	0.1379745
## (Intercept)	2.0	1.9967916	2.7235037	2.6711174
## x1	-1.9	-1.8990528	-1.9996477	-1.4179726
## x2	0.8	0.7998454	0.8260788	0.7005770
## G: x1	1.5	1.4982137	1.3591351	0.9242272
## G: x2	-1.2	-1.1994937	-1.0790096	-0.6846019
## sigma	1.5	1.4974801	1.6256067	1.3795906

The estimator of the count data model seems unbiased while the SART and the SAR models underestimate the peer effect.

## 5 Examples with endogenous network

Peer effect estimation is generally based on the assumption of exogeneity of the adjacency matrix. This means that the probability of link formation is not correlated to the error term in the count data model. Such an assumption is strong as the link formation probability may depend on unobserved characteristics (e.g., gregariousness) that also influence the outcome. In this section, I simulate data with endogenous network (which violates the assumption). I then show that the peer effect is overestimated when one does not control for the endogeneity of the network. I also present a method to control for the endogeneity. Finally, I use Monte Carlo simulations to prove that this method performs well.

### 5.1 Data simulation

I assume three sub-networks. The number of individuals in each sub-network is randomly chosen between 100 and 500.

```

rm(list = ls())
set.seed(2020)
# Groups' size
M      <- 3 # Number of sub-groups
nvec   <- round(runif(M, 100, 500))
print(nvec)

## [1] 359 258 347

n      <- sum(nvec)
print(n)

## [1] 964

# Parameters
lambda <- 0.4          # peer effect
beta   <- c(2, -1.9, 0.8) # own effects
gamma  <- c(1.5, -1.2)   # contextual effects
sigma  <- 1.5           # standard deviation of epsilon
theta  <- c(lambda, beta, gamma, sigma)

# X
data   <- data.frame(x1 = rnorm(n, 1, 1), x2 = rexp(n, 0.4))

```

The network matrix follows the dyadic linking model presented in [Houndetoungan \(2020\)](#). Let  $\mathbf{A}$  be the matrix of links such that  $A_{ij} = 1$  if  $i$  knows  $j$  and  $A_{ij} = 0$ . In other words,  $A_{ij} = 1$  if  $G_{ij} = \frac{1}{n_i}$ . It is easier to work with  $\mathbf{A}$  (binary data) in the network formation model. However, in the count data model, I use  $\mathbf{G}$  as row-normalized equivalent of  $\mathbf{A}$ .

The probability of link formation,  $P_{ij}$  depends on  $\Delta x_{1ij} = |x_{1i} - x_{1j}|$  and  $\Delta x_{2ij} = |x_{2i} - x_{2j}|$  (observed dyad-specific variables) as well as on unobserved individual-level attributes  $\mu_i$  and  $\mu_j$ . Typically, let  $a_{ij}^*$  defined by

$$a_{ij}^* = \Delta \mathbf{x}_{ij}' \bar{\boldsymbol{\beta}} + \mu_i + \mu_j + \varepsilon_{ij}^*,$$

where  $\varepsilon_{ij}^* \sim \text{logistic}$  distribution. I assume that  $A_{ij} = 1$  if  $a_{ij}^* > 0$ . In that case,  $P_{ij}$  is given by

$$P_{ij} = \frac{\exp(\Delta \mathbf{x}_{ij}' \bar{\boldsymbol{\beta}} + \mu_i + \mu_j)}{1 + \exp(\Delta \mathbf{x}_{ij}' \bar{\boldsymbol{\beta}} + \mu_i + \mu_j)}.$$

I also assume that  $\mu_i$  is random. If  $i$  is from the  $s$ -th sub-network, then  $\mu_i \sim \mathcal{N}(u_{\mu s}, \sigma_{\mu s}^2)$ . The mean and the variance of  $\mu_i$  vary across the sub-networks. This is a way to control for the sub-network heterogeneity as fixed effects in the link formation probability.

```

# Parameter for network model
betanet <- c(-2.8, -1.5) # beta
Glist   <- list()        # adjacency matrix row normalized
Network <- list()        # adjacency matrix row non-normalized
dX      <- matrix(0, 0, 2) # observed dyad-specific variables
mu      <- list()        # unobserved individual-level attribute
uu      <- runif(M, -1, 1) # mean of uu in each sub-network
sigma2u <- runif(M, 0.5, 4) # variance of uu in each sub-network

# Network
for (m in 1:M) {
  nm      <- nvec[m]
  mum     <- rnorm(nm, uu[m], sqrt(sigma2u[m]))

```



```

Z1      <- matrix(0, nm, nm)
Z2      <- matrix(0, nm, nm)

for (i in 1:nm) {
  for (j in 1:nm) {
    Z1[i, j] <- abs(data$x1[i] - data$x1[j])
    Z2[i, j] <- abs(data$x2[i] - data$x2[j])
  }
}

Gm      <- 1*((Z1*betanet[1] + Z2*betanet[2] +
               kronecker(mum, t(mum), "+") + rlogis(nm^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))

Network[[m]] <- Gm
rs      <- rowSums(Gm); rs[rs == 0] <- 1
Gm      <- Gm/rs
Glist[[m]] <- Gm
mu[[m]] <- mum
}
mu      <- unlist(mu)

```

To simulate the dependent variable, I use  $\mu$ , the vector of  $\mu_i$  as additional explanatory variable in the count variable model. I set that  $Cor(\mu_i, \varepsilon_i) = \rho$  and  $Cor(\sum_{j=1}^n G_{ij}\mu_i, \varepsilon_i) = \bar{\rho}$ . In that case,  $\varepsilon_i = \rho\sigma_\varepsilon\tilde{\mu}_i + \bar{\rho}\sigma_\varepsilon\tilde{\mu}_i + \tilde{\nu}_i$ , where  $\tilde{\mu}_i = \frac{\mu_i - u_{\mu s}}{\sigma_{\mu s}}$ ,  $\tilde{\mu}_i = \sum_{j=1}^n G_{ij}\tilde{\mu}_j$  is the average of  $\tilde{\mu}_i$  among  $i$ 's friends and  $\tilde{\nu}_i$  is the new error term following normal distribution of variance  $\bar{\sigma}_\varepsilon^2 = (1 - \rho^2 - \bar{\rho}^2)\sigma_\varepsilon^2$ .

```

tmu      <- (mu - rep(uu, nvec))/sqrt(rep(sigma2u, nvec))
data$tmu <- tmu
rho      <- 0.24
rhobar   <- 0.18
thetanet <- c(lambda, beta, sigma*rho, gamma, sigma*rhobar,
               sigma*(1 - rho - rhobar))
ytmp     <- simCDnet(formula = ~ x1 + x2 + tmu | x1 + x2 + tmu,
                     Glist = Glist, theta = thetanet, data = data)
y        <- ytmp$y
# Add y to data
data$y   <- y
# Summarize y
summary(y)

```

```

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.000   1.000   2.000   2.694   4.000  18.000

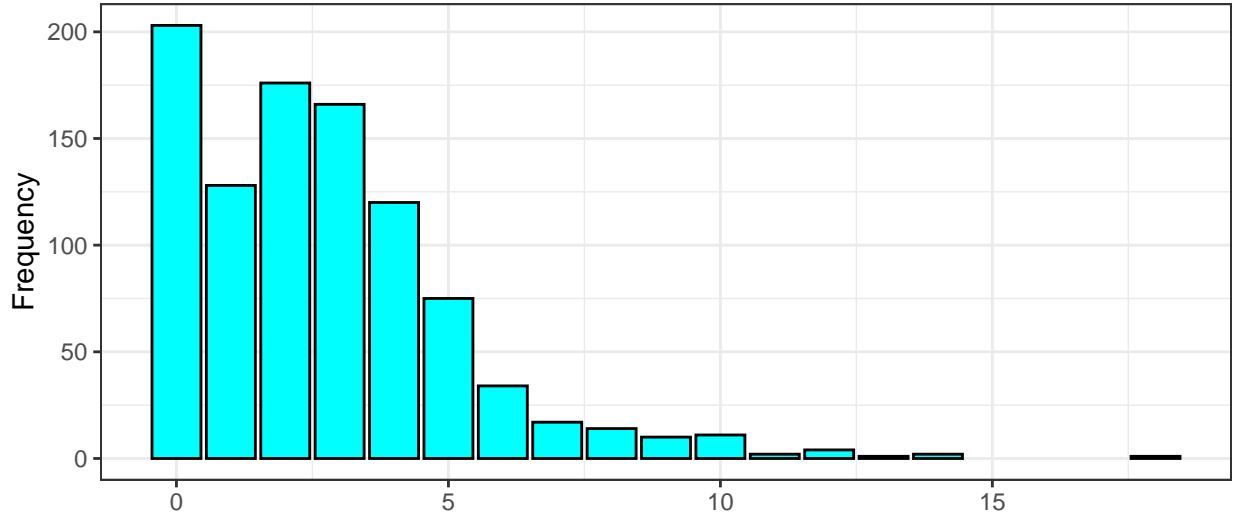
```

```

# Plot data histogram
print(ggplot(data = data.frame(y = y), aes(x = y)) +
      geom_bar(color = "black", fill = "cyan") +

```

```
theme_bw() + xlab("") + ylab("Frequency"))
```



In real life,  $\tilde{\mu}_i$  and  $\bar{\mu}_i$  are not observed and they are included in the error term  $\varepsilon_i$ . This implies that the network is endogenous.

## 5.2 Estimation

When the endogeneity of the network is not taken into account, the peer effect is overestimated. The reason is that the peer effect also captures other effects. The model considers any common shock on  $\tilde{\mu}_i$  and  $\bar{\mu}_i$  as peer effect. In the example below, the peer effect is estimated at 0.49 when I do not control for the endogeneity of the network.

```
# Count data model
CDexo <- CDnetNPL(formula = y ~ x1 + x2, contextual = TRUE, Glist = Glist,
                  optimizer = "optim", data = data, npl.ctr = list(print = FALSE))
summary(CDexo)
```

```
## Count data Model with Social Interactions
##
## Method: Nested pseudo-likelihood (NPL)
## Iteration: 22
##
## Network:
## Number of groups      : 3
## Sample size          : 964
## Average number of friends: 27.30809
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## lambda      0.487503   0.037720  12.92   <2e-16 ***
## (Intercept) 1.825234   0.141787  12.87   <2e-16 ***
## x1          -1.947378   0.042677 -45.63   <2e-16 ***
## x2           0.803085   0.015453  51.97   <2e-16 ***
## G: x1        1.705766   0.076044  22.43   <2e-16 ***
## G: x2       -1.201023   0.026497 -45.33   <2e-16 ***
##
## Marginal Effects:
##              Estimate Std. Error t value Pr(>|t|)
```

```
## lambda      0.410015    0.032023    12.80    <2e-16 ***
## (Intercept) 1.535114    0.118774    12.92    <2e-16 ***
## x1          -1.637843    0.042362   -38.66    <2e-16 ***
## x2           0.675435    0.014767    45.74    <2e-16 ***
## G: x1        1.434635    0.067551    21.24    <2e-16 ***
## G: x2       -1.010121    0.025133   -40.19    <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## sigma: 0.9333558
## log pseudo-likelihood: -1139.806
```

To correct the endogeneity,  $\tilde{\mu}_i$  and  $\tilde{\mu}_j$  should be included in the model as additional explanatory variables. However, these variables are not observed.

I use Markov Chain Monte Carlo (MCMC) to estimate the parameters of the dyadic linking model (these include the unobserved individual-level attributes  $\mu_i$ ). The estimation can be done using the function `netformation`.

```
# Dyadic linking model
net <- netformation(network = Network, formula = ~ dX, fixed.effects = TRUE,
                    mcmc.ctr = list(burnin = 1000, iteration = 5000))
```

```
##
##
## The program successfully executed
##
## *****SUMMARY*****
## n.obs       : 314890
## n.links     : 26325
## K           : 2
## Fixed effects : Yes
## Burnin      : 1000
## Iteration   : 6000
##
## Elapsed time : 0 HH 4 mm 29 ss
##
## Average acceptance rate
##                beta: 0.274125
##                mu: 0.2697619
```

I randomly choose some parameters and present their posterior distribution.

```
# plot simulations
par(mfrow = c(4,2), mar = c(2, 2, 2, 1.9))
plot(net$posterior$beta[,1], type = "l", ylim = c(-2.9, -2.6), col = "blue",
     main = bquote(beta[1]), ylab = "")
abline(h = betanet[1], col = "red")

plot(net$posterior$beta[,2], type = "l", ylim = c(-1.6, -1.4), col = "blue",
     main = bquote(beta[2]), ylab = "")
abline(h = betanet[2], col = "red")

plot(net$posterior$mu[,10], type = "l", col = "blue",
     main = bquote(mu[10]), ylab = "")
abline(h = mu[10], col = "red")
```

```

plot(net$posterior$mu[,542], type = "l", col = "blue",
     main = bquote(mu[542]), ylab = "")
abline(h = mu[542], col = "red")

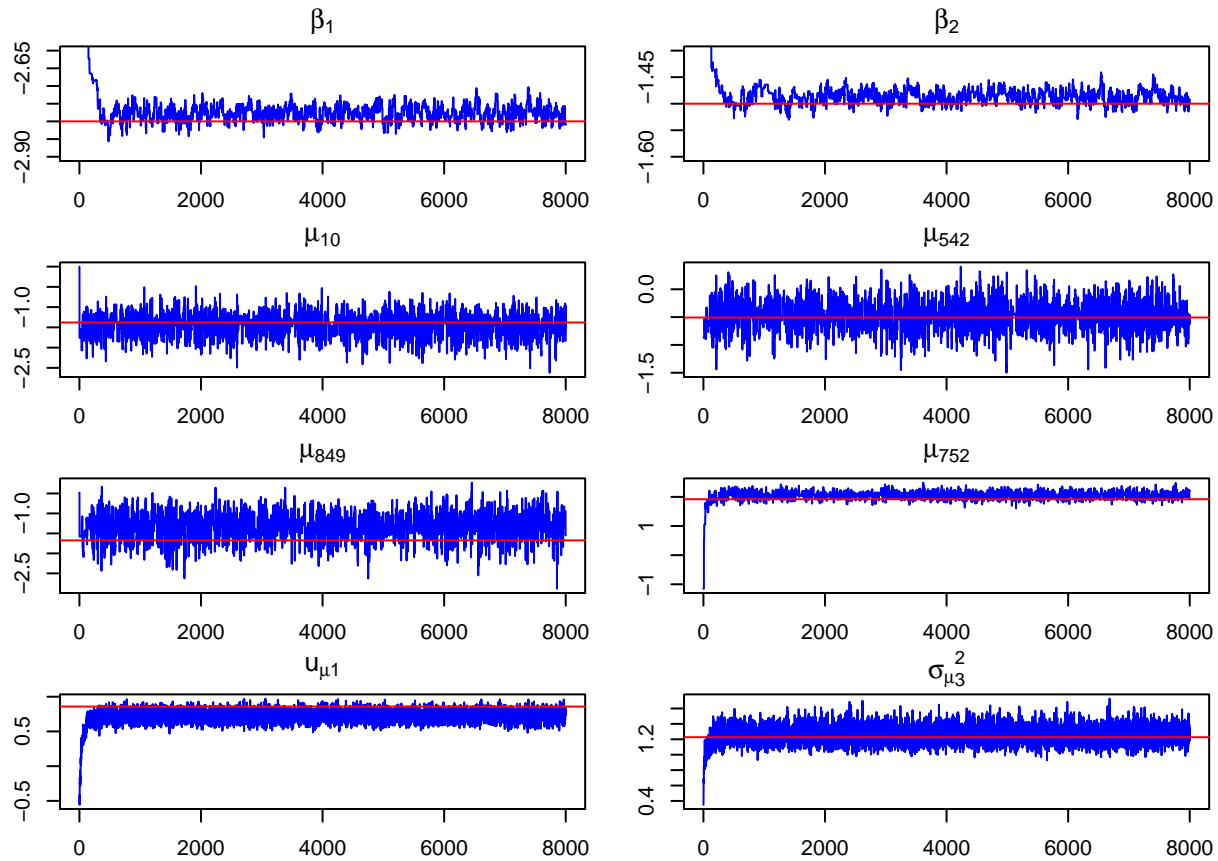
plot(net$posterior$mu[,849], type = "l", col = "blue",
     main = bquote(mu[849]), ylab = "")
abline(h = mu[849], col = "red")

plot(net$posterior$mu[,752], type = "l", col = "blue",
     main = bquote(mu[752]), ylab = "")
abline(h = mu[752], col = "red")

plot(net$posterior$uu[,1], type = "l", col = "blue",
     main = bquote(u[mu][1]), ylab = "")
abline(h = uu[1], col = "red")

plot(net$posterior$sigmamu2[,3], type = "l", col = "blue",
     main = bquote(sigma[mu][3]^2), ylab = "")
abline(h = sigma2u[3], col = "red")

```



It stands out that the MCMC converges quickly and the simulations (plotted in blue) are pretty close to the true values (red line).

Using simulations from the posterior distribution, I can construct good estimators for  $\tilde{\mu}_i$  and  $\bar{\tilde{\mu}}_i$  and use them as additional supplementary explanatory variables. In the next example, I use the simulation with the highest posterior density to estimate  $\tilde{\mu}_i$  and  $\bar{\tilde{\mu}}_i$ .

```

t      <- which.max(net$posterior$log.density)
print(t)

## [1] 1683

muest      <- net$posterior$mu[t,]
uuest      <- net$posterior$uu[t,]
sigma2uest <- net$posterior$sigmamu2[t,]
tmuest     <- (muest - rep(uuest, nvec))/sqrt(rep(sigma2uest, nvec))
data$tmuest <- tmuest
CDendo     <- CDnetNPL(formula = y ~ x1 + x2 + tmuest, contextual = TRUE,
                       Glist = Glist, optimizer = "optim", data = data,
                       npl.ctr = list(print = FALSE))
summary(CDendo)

## Count data Model with Social Interactions
##
## Method: Nested pseudo-likelihood (NPL)
## Iteration: 19
##
## Network:
## Number of groups      : 3
## Sample size           : 964
## Average number of friends: 27.30809
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## lambda      0.396270   0.039201  10.11  <2e-16 ***
## (Intercept) 1.872723   0.142839  13.11  <2e-16 ***
## x1          -1.934278   0.040683  -47.55  <2e-16 ***
## x2           0.806577   0.014753   54.67  <2e-16 ***
## tmuest       0.342133   0.035291    9.69  <2e-16 ***
## G: x1        1.602878   0.076393   20.98  <2e-16 ***
## G: x2       -1.208013   0.026084  -46.31  <2e-16 ***
## G: tmuest    0.280042   0.079683    3.51 0.000441 ***
##
## Marginal Effects:
##              Estimate Std. Error t value Pr(>|t|)
## lambda      0.333358   0.033149   10.06  <2e-16 ***
## (Intercept) 1.575409   0.119991   13.13  <2e-16 ***
## x1          -1.627191   0.040520  -40.16  <2e-16 ***
## x2           0.678525   0.014304   47.44  <2e-16 ***
## tmuest       0.287816   0.030296    9.50  <2e-16 ***
## G: x1        1.348404   0.067310   20.03  <2e-16 ***
## G: x2       -1.016228   0.024853  -40.89  <2e-16 ***
## G: tmuest    0.235582   0.066910    3.52 0.00043 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## sigma: 0.880119
## log pseudo-likelihood: -1094.926

```

The coefficients of  $\tilde{\mu}_i$  and  $\bar{\mu}_i$  are significant. This confirms that the network is endogenous. Moreover, the peer effect is estimated at 0.40, which is much better than the previous estimate.

The standard errors computed in this example are not valid because they assume that  $\tilde{\mu}_i$  and  $\tilde{\mu}_i$  are observed. To correct the standard error, I replicate simulations of  $\tilde{\mu}_i$  and  $\tilde{\mu}_i$  with replacement from the posterior distribution in order to take into account the variance of the MCMC.

```
fendo    <- function(s) {
  t      <- sample(3001:8000, 1)
  datat  <- data
  mus    <- net$posterior$mu[t,]
  uus    <- rep(net$posterior$uu[t,], nvec)
  sus    <- rep(net$posterior$sigmamu2[t,], nvec)
  tmu    <- (mus - uus)/sqrt(sus)
  datat$tmu <- tmu

  CDnet  <- CDnetNPL(formula = y ~ x1 + x2 + tmu, contextual = TRUE,
                    Glist = Glist, optimizer = "optim", data = datat,
                    npl.ctr = list(print = FALSE))

  summary(CDnet, Glist = Glist, data = datat)
}

n.cores  <- 32
replic   <- 1000 #Number of replications
out.endo <- mclapply(1:replic, fendo, mc.cores = n.cores)
# The output of out.endo is a list of objects from "summary.CDnetNPL" class
# Let's set the class of out.endo as "summary.CDnetNPLs"
class(out.endo) <- "summary.CDnetNPLs"
# I can now summarize the results using print
# Object from "summary.CDnetNPL" has a print method
print(out.endo)

## Count data Model with Social Interactions
##
## Method: Replication of Nested pseudo-likelihood (NPL)
## Replication: 1000
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## lambda      0.402133   0.040005  10.05  <2e-16 ***
## (Intercept)  1.864045   0.146209  12.75  <2e-16 ***
## x1          -1.935345   0.041119 -47.07  <2e-16 ***
## x2           0.806629   0.014940  53.99  <2e-16 ***
## tmu          0.337809   0.037415   9.03  <2e-16 ***
## G: x1        1.611186   0.078309  20.57  <2e-16 ***
## G: x2       -1.212639   0.026483 -45.79  <2e-16 ***
## G: tmu        0.255580   0.088880   2.88  0.00403 **
##
## Marginal Effects:
##           Estimate Std. Error t value Pr(>|t|)
## lambda      0.338501   0.033852  10.00  <2e-16 ***
## (Intercept)  1.569115   0.123193  12.74  <2e-16 ***
## x1          -1.629105   0.040575 -40.15  <2e-16 ***
## x2           0.678992   0.014350  47.32  <2e-16 ***
## tmu          0.284351   0.031994   8.89  <2e-16 ***
## G: x1        1.356236   0.068747  19.73  <2e-16 ***
## G: x2       -1.020757   0.025080 -40.70  <2e-16 ***
```

```
## G: tmu      0.215120  0.074660  2.88  0.00396  **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## sigma: 0.8792079
## log pseudo-likelihood:
##      min      mean      max
## -1104.369 -1094.693 -1085.772
```

The standard errors are slightly greater than the previous estimate.

### 5.3 Monte Carlo Simulations

One simulation is not sufficient to confirm that the method used to correct the endogeneity performs well. In this section, I use Monte Carlo simulations to assess the performance of this method. I compare the estimates when the network is assumed exogenous to these when I control for the endogeneity.

I build the following Monte Carlo function which simulates data based on endogenous network, and estimates the model by assuming that the network is exogenous and then endogenous.

```
fMCendo <- function(s) {
  # parameters
  M      <- 3
  nvec   <- rep(500, 3)
  n      <- sum(nvec)

  lambda <- 0.4          # peer effect
  beta   <- c(2, -1.9, 0.8) # own effects
  gamma  <- c(1.5, -1.2)   # contextual effects
  sigma  <- 1.5           # standard deviation of epsilon
  theta  <- c(lambda, beta, gamma, sigma)

  data <- data.frame(x1 = rnorm(n, 1, 1), x2 = rexp(n, 0.4))

  # Network
  betanet <- c(-2.8, -1.5) # beta
  Glist   <- list()        # adjacency matrix row normalized
  Network <- list()        # adjacency matrix row non-normalized
  dX      <- matrix(0, 0, 2) # observed dyad-specific variables
  mu      <- list()        # unobserved individual-level attribute
  uu      <- runif(M, -1, 1) # mean of uu in each sub-network
  sigma2u <- runif(M, 0.5, 4) # variance of uu in each sub-network

  for (m in 1:M) {
    nm      <- nvec[m]
    mum     <- rnorm(nm, uu[m], sqrt(sigma2u[m]))
    Z1      <- matrix(0, nm, nm)
    Z2      <- matrix(0, nm, nm)

    for (i in 1:nm) {
      for (j in 1:nm) {
        Z1[i, j] <- abs(data$x1[i] - data$x1[j])
        Z2[i, j] <- abs(data$x2[i] - data$x2[j])
      }
    }
  }
}
```

```

Gm          <- 1*((Z1*betanet[1] + Z2*betanet[2] +
                  kronecker(mum, t(mum), "+") + rlogis(nm^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))

Network[[m]] <- Gm
rs          <- rowSums(Gm); rs[rs == 0] <- 1
Gm          <- Gm/rs
Glist[[m]]  <- Gm
mu[[m]]     <- mum
}
mu          <- unlist(mu)

# Data
tmu         <- (mu - rep(uu, nvec))/sqrt(rep(sigma2u, nvec))
data$tmu    <- tmu
rho         <- 0.24
rhobar      <- 0.18
thetanet    <- c(lambda, beta, sigma*rho, gamma, sigma*rhobar,
                  sigma*(1 - rho - rhobar))
ytmp        <- simCDnet(formula = ~ x1 + x2 + tmu | x1 + x2 + tmu,
                        Glist = Glist, theta = thetanet, data = data)
y           <- ytmp$y
data$y      <- y

# Count data model
CDexo <- CDnetNPL(formula = y ~ x1 + x2, contextual = TRUE, Glist = Glist,
                  optimizer = "optim", data = data, npl.ctr = list(print = FALSE))

# Dyadic linking model
net    <- netformation(network = Network, formula = ~ dX, fixed.effects = TRUE,
                        mcmc.ctr = list(burnin = 1000, iteration = 2000), print = FALSE)

# Endogeneity
t      <- which.max(net$posterior$log.density)
muest  <- net$posterior$mu[t,]
uuest  <- net$posterior$uu[t,]
sigma2uest <- net$posterior$sigmamu2[t,]
tmuest <- (muest - rep(uuest, nvec))/sqrt(rep(sigma2uest, nvec))
data$tmuest <- tmuest
CDendo <- CDnetNPL(formula = y ~ x1 + x2 + tmuest, contextual = TRUE,
                  Glist = Glist, optimizer = "optim", data = data,
                  npl.ctr = list(print = FALSE))
c(CDexo$estimate, CDendo$estimate)
}

```

I now run the function `fMCendo` 1000 times and compute the average of both estimators.

```

n.cores      <- 5
replic       <- 1000 #Number of replications

```



```

out.mcendo      <- mclapply(1:replc, fMCendo, mc.cores = n.cores)
out.mcendo      <- apply(t(do.call(cbind, out.mcendo)), 2, mean)
out.endo        <- cbind(thetanet, c(out.mcendo[c(1:4, NA, 5:6, NA, 7)]),
                           out.mcendo[8:16])
rownames(out.endo) <- names(out.mcendo[8:16])
colnames(out.endo) <- c("TrueValue", "Endo-Not-Controlled", "Endo-Controlled")
print(out.endo)
save(out.endo, file = "out.mcendo.Rdata")

```

##	TrueValue	Endo-Not-Controlled	Endo-Controlled
## lambda	0.40	0.5201007	0.4186179
## (Intercept)	2.00	1.7957977	1.9745290
## x1	-1.90	-1.9077019	-1.8984809
## x2	0.80	0.8019128	0.8002151
## tmuest	0.36	NA	0.3344702
## G: x1	1.50	1.6644998	1.5205194
## G: x2	-1.20	-1.1805244	-1.2008929
## G: tmuest	0.27	NA	0.2286079
## sigma	0.87	0.9303622	0.8780438

The results prove that the method used to correct the endogeneity performs fairly well. The average of the estimates is 0.42 while the true value is 0.40. There is still a small bias. This is certainly due to the number of iterations of the MCMC which is low. Indeed, I use the iteration with the highest posterior density to estimate  $\tilde{\mu}_i$  and  $\tilde{\mu}_i$ . Since the number of iterations is low, the estimates may not be very good. The more the number of iterations, the better the simulation with highest posterior density for approximating  $\tilde{\mu}_i$  and  $\tilde{\mu}_i$ .

In contrast, the peer effect is overestimated when the network is assumed exogenous. The average of the estimates is 0.52.

## 6 Conclusion

This paper provides technical details on the package **CDatanet**. It shows with simple and practical examples how to use the package. It provides comparison of the model with the SART and the SAR models. It also shows with Monte Carlo simulations how the model performs when the network matrix is exogenous and endogenous. Simulation results prove that the peer effect is overestimated when the network is endogenous. Lastly, it presents a way to control for the endogeneity of the network.

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