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Network inference for truncated gaussian data

Anne Gégout, Aurélie Gueudin and Clémence Karmann

Université de Lorraine, Inria Nancy Grand Est, FRANCE

anne.gegout-petit@univ-lorraine.fr

EMS 2019

Palermo

Introduction

- Infer network defined by conditional dependencies

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- Infer network defined by conditional dependencies
- Gaussian variables zero inflated by double truncation
- Applications for the modelling of interactions between microbacterial populations
 - left truncation: replication phenomena
 - right truncation: non restrictive hypothesis for theoretical results !

Content

- 1 Modelling
- 2 Estimation process
 - Covariance matrix estimation
 - Precision matrix estimation
- 3 Theoretical results
- 4 Simulation studies

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Modelling

Modelling

Let $\mathbf{X} \sim \mathcal{N}_p(0, \Sigma^*)$ be a gaussian p -vector with $\Sigma_{jj}^* = 1$ for all j . \mathbf{X} is not observed but we observe \mathbf{Y} defined from \mathbf{X} by:

$Y_j = \mathbb{1}_{a_j \leq X_j \leq b_j} X_j$ where $a_j < b_j$.

A non directed graph structure is given by the inverse of the covariance matrix $\Theta^* := (\Sigma^*)^{-1}$:

$$\begin{aligned} X_j \longleftrightarrow X_k &\iff X_j \not\perp\!\!\!\perp X_k \mid (X_l)_{l \neq j, k} \\ &\iff \text{cor}(X_j, X_k \mid (X_l)_{l \neq j, k}) \neq 0 \\ &\iff \Theta_{jk}^* \neq 0. \end{aligned}$$

Aim

Aim

Infer the latent graph structure given by the precision matrix Θ^* of the gaussian vector \mathbf{X} from the observations of the truncated vector \mathbf{Y} .

Theoretical tools - Pairs likelihood

Let us look at the likelihood $\mathcal{L}_{jk}(\Sigma_{jk}^*, y)$ of the pairs (Y_j, Y_k) , $j < k$ where :

$$\mathcal{L}_{jk}(\sigma, y) = \sum_{a,b=0}^1 \phi_{ab,jk}(\sigma, y_j, y_k) n_{ab}(y_j, y_k),$$

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- $n_{ab}(y_j, y_k) = \mathbb{1}_{\zeta_j=a, \zeta_k=b}$ où $\zeta_l = \begin{cases} 1 & \text{si } y_l \in [a_l, b_l] \setminus \{0\}, \\ 0 & \text{si } y_l = 0. \end{cases}$

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- $\phi_{10,jk}(\sigma, y_j, y_k) = \phi_{10,jk}(\sigma, y_j) = \int_{[a_k, b_k]^c} f(y_j, y, \sigma) dy$

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- $\phi_{00,jk}(\sigma, y_j, y_k) = \phi_{00,jk}(\sigma) = \iint_{[a_j, b_j]^c \times [a_k, b_k]^c} f(x, y, \sigma) dx dy.$

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Context

Let $\mathbf{Y} := (Y^{(1)}, \dots, Y^{(n)})$ be an i.i.d. n -sample du vecteur Y . For every $j < k$, let us denote:

- $\mathcal{L}_{jk}^{(n)}(\Sigma_{jk}^*, \mathbf{y})$ the likelihood of the pairs sample $((Y_j^{(i)}, Y_k^{(i)}))_{1 \leq i \leq n}$ given by:

$$\mathcal{L}_{jk}^{(n)}(\sigma, \mathbf{y}) = \prod_{i=1}^n \mathcal{L}_{jk}(\sigma, y^{(i)}).$$

- $L_{jk}^{(n)}(\Sigma_{jk}^*, \mathbf{y})$ the log-likelihood $L_{jk}^{(n)}(\Sigma_{jk}^*, \mathbf{y}) = \log(\mathcal{L}_{jk}^{(n)}(\sigma, \mathbf{y}))$

Step 1: covariance matrix Σ^*

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\rightsquigarrow estimator of Σ^* term to term from the pairs (Y_j, Y_k) . We estimate each coefficients $\tilde{\Sigma}_{jk}^{(n)}$ by maximising the log-likelihood of the sample $((Y_j^{(i)}, Y_k^{(i)}))_{i=1, \dots, n}$.

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Estimator of the covariance matrix

Estimator $\tilde{\Sigma}^{(n)}$ of Σ^* is defined by:

$$\tilde{\Sigma}_{jk}^{(n)} = \underset{|\sigma| \leq 1}{\operatorname{argmax}} L_{jk}^{(n)}(\sigma, \mathbf{y}). \quad (1)$$

Step 2: precision matrix Θ^*

Idea : estimate Θ^* thanks to the graphical Lasso (Friedman et al. (2007)) for the GGM

\rightsquigarrow is to maximize the penalized log-likelihood of the Gaussian model.

$$\hat{\Theta}^{(n)} = \operatorname{argmax}_{\Theta \succ 0} \log \det(\Theta) - \operatorname{trace}(\Theta \hat{\Sigma}^{(n)}) - \lambda_n \|\Theta\|_{1,\text{off}}. \quad (2)$$

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Tools

Step 1: Mei & al (2017), *under suitable assumptions, good properties of the population risk can be carried to the empirical risk, even in a non-convex case*

\rightsquigarrow control of $|\tilde{\Sigma}_{j,k}^{(n)} - \Sigma_{j,k}^*|$

Tools

Step 1: Mei & al (2017),
 \rightsquigarrow control of $|\tilde{\Sigma}_{j,k}^{(n)} - \Sigma_{j,k}^*|$

Step 2: Ravikumar & al (2011), *estimating the concentration matrix under sparsity conditions without specific distributional assumptions, but rather analyze the estimator in terms of the tail behavior of $\max_{j,k} |\tilde{\Sigma}_{j,k}^{(n)} - \Sigma_{j,k}^*|$*

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(H2) Let $j < k$. Let g be a function:

$$\sigma \in [-1 + \delta, 1 - \delta] \mapsto \mathbb{E}\left(L_{jk}^{(n)}(\sigma, \mathbf{y})\right).$$

- $(-1 + \delta)$ et $(1 - \delta)$ are not critical points of g ,
- g admits a finite number of critical points,
- all the critical points of g , different from Σ_{jk}^* , are non-degenerated, that is:

$$\sigma \neq \Sigma_{jk}^*, \quad g'(\sigma) = 0 \Rightarrow g''(\sigma) \neq 0.$$

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(H3) Technical (not written). The underlying intuition is to limit the influence of "non-edged" terms on edge terms.

Intermediate result on the estimated covariance matrix $\tilde{\Sigma}^{(n)}$

Proposition

Under **(H1)** and, **(H2)**, let $0 < \rho < 1$. There exist known constants B , C and D such that if n satisfies $\frac{n}{\log n} \geq C \log\left(\frac{B}{\rho}\right)$, then the estimated covariance matrix $\tilde{\Sigma}^{(n)}$ satisfies:

$$\mathbb{P}\left(\|\tilde{\Sigma}^{(n)} - \Sigma^*\|_{\infty} \geq D \sqrt{\frac{\log n}{n} \log\left(\frac{B}{\rho}\right)}\right) \leq \frac{\rho(\rho-1)}{2} \rho,$$

where $\|A\|_{\infty} = \max_{j,k \in \{1, \dots, p\}} |A_{jk}|$ is the infinite norm of matrix $A \in \mathbb{R}^{p^2}$.

\rightsquigarrow Mei *et al.* (2017)

Final result about $\tilde{\Theta}^{(n)}$

Theorem

Under **(H1)**, **(H2)** et **(H3)**. Let $c > 2$. There exist known constants B , C and D such that for all n satisfying $\frac{n}{\log n} > f(B, C, D, c, \Sigma^*)$ and

$\lambda_n \propto \sqrt{\frac{\log n}{n} \log(Bp^c)}$, we have with probability $1 - \frac{1}{p^{c-2}}$:

(a) $\|\tilde{\Theta}^{(n)} - \Theta^*\|_\infty \leq D \sqrt{\frac{\log n}{n} \log(Bp^c)}$.

(b) $E(\tilde{\Theta}^{(n)}) \subset E(\Theta^*)$ and vertices (j, k) is correctly detected as soon as: $|\Theta_{jk}^*| > D \sqrt{\frac{\log n}{n} \log(Bp^c)}$.

\rightsquigarrow Ravikumar *et al.* (2011)

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Simulations design

- $p = 100$ covariates, $n = 500$ observations

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 $X_1 \longleftrightarrow X_2 \longleftrightarrow \dots \longleftrightarrow X_{100}$

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- Different truncation thresholds:
 - Identical thresholds : $a = -0.5, b = 2$
 - Non identical thresholds $a = \text{seq}(-1, 0), b = \text{seq}(0.5, 3)$

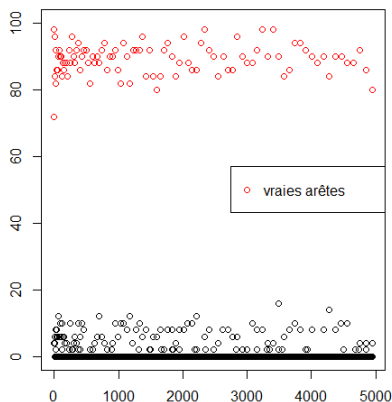
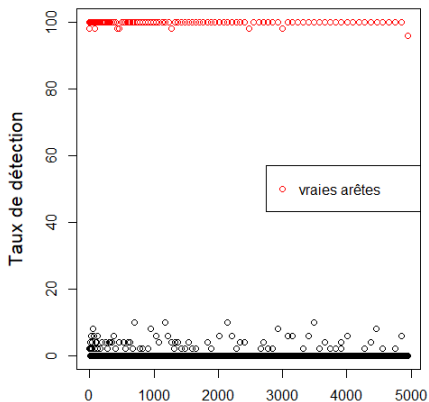
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 - Non identical thresholds $a = \text{seq}(-1, 0), b = \text{seq}(0.5, 3)$
- Detection rate over 50 repetitions and comparison with naive graphical Lasso directly on truncated data \mathbf{Y} .

$a = -0.5 ; b = 2$

Nous

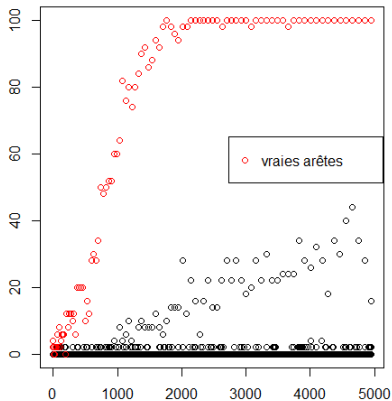
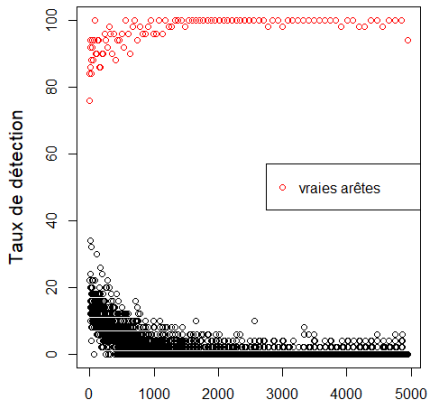
Graphical Lasso

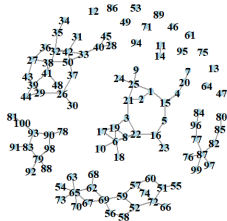


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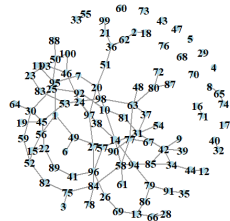
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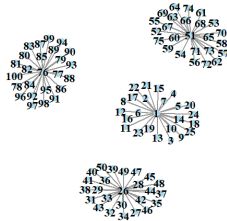




(a) Structure “cluster”.



(b) Structure “random”.



(c) Structure “hub”.

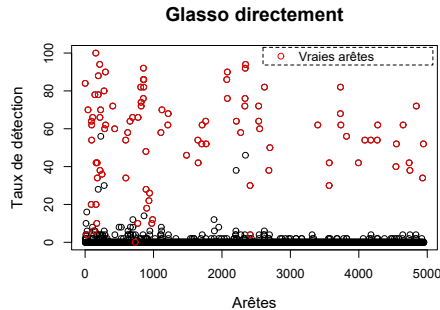
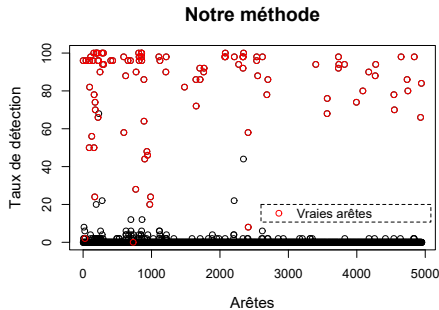


Figure: Detection rates obtained by our method (estimated truncation points) and by the graphical Lasso applied directly to the truncated data. The configurations of the truncation points are "identical only". Detection rates are obtained over 50 independent repetitions for $n = 500$ observations of $p = 100$ variables. "cluster" structure; red = true edges.

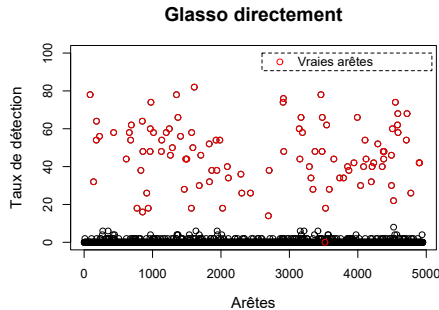
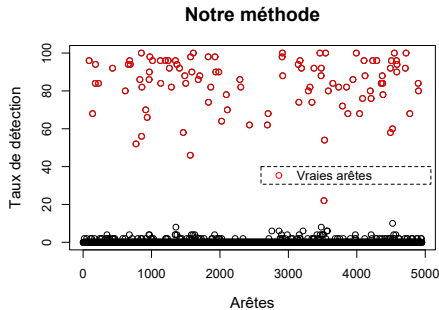


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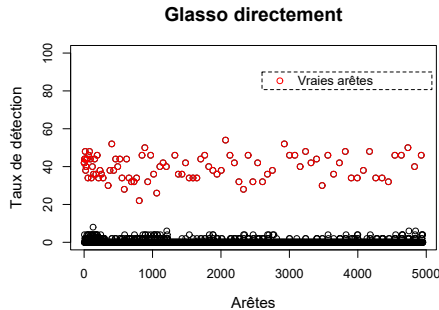
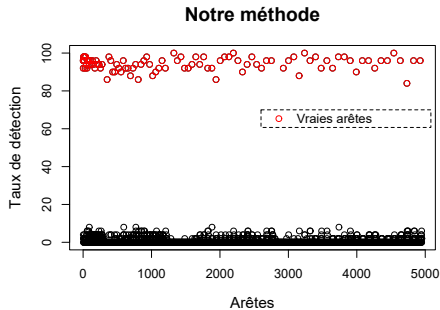




Figure: Detection rates obtained by our method (estimated truncation points) and by the graphical Lasso applied directly to the truncated data. The configurations of the truncation points are "identical only". Detection rates are obtained over 50 independent repetitions for $n = 500$ observations of $p = 100$ variables. "hub" structure; red = true edges.

Grazie mille !

-  Mei S., Bei Y., and Montanari A. The landscape of empirical risk for non-convex losses. *arXiv preprint arXiv:1607.06534*, 2017.
-  Ravikumar P., Wainwright M. J., Raskutti G., and Yu B. High-dimensional covariance estimation by minimizing ℓ_1 -penalized log-determinant divergence. *Electronic Journal of Statistics*, 5:935-980, 2011.