# BOOTSTRAP RESULTS

CLEMENT CARRIER

## Bootstrap

We simulate the data by choosing, the sparsity of the true parameters (number of non zero coefficient), the number of covariates, the number of observations and the nature of the noise (here we choose iid N(0,1)).

Table 1. Simulation Result

| beta=0.9 | | iid1 | | | | | AR(1) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Model | X.p.n. | lenght | cov1 | fn | biais1 | biais2 | lenght2 | cov1.1 | fn2 | biais1.1 | biais2.1 |
| 1 | (50,100) | 0.427 | 0.345 | 33.386 | 0.273 | 0.330 | 0.259 | 0.138 | 3.399 | 0.216 | 0.162 |
| 2 | (100,100) | 0.394 | 0.386 | 49.198 | 0.294 | 0.383 | 0.273 | 0.079 | 10.163 | 0.263 | 0.195 |
| 3 | (200,100) | 0.360 | 0.432 | 63.837 | 0.312 | 0.429 | 0.271 | 0.047 | 20.786 | 0.299 | 0.227 |

In the following one, we increase the number of nonzero parameter (5 and 10).

```
## Warning in readChar(con, 5L, useBytes = TRUE): impossible d'ouvrir le fichier
compress 'data/2/mc2.Rdata', cause probable :  'No such file or directory'
## Error in readChar(con, 5L, useBytes = TRUE): impossible d'ouvrir la connexion
## Warning in readChar(con, 5L, useBytes = TRUE): impossible d'ouvrir le fichier
compress 'data/2/mc3.Rdata', cause probable :  'No such file or directory'
## Error in readChar(con, 5L, useBytes = TRUE): impossible d'ouvrir la connexion
```

Table 2. Simulation Result 2

| | | iid5 beta =1 | | | | | iid10 beta =1 n=200 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Model | X.p.n. | lenght | cov1 | fn | biais1 | biais2 | lenght2 | cov1.1 | fn2 | biais1.1 | biais2.1 |
| 1 | (50,100) | 0.452 | 0.564 | 263.582 | 0.272 | 0.476 | 0.223 | 0.300 | 905.668 | 0.230 | 0.709 |
| 2 | (100,100) | 0.394 | 0.386 | 49.198 | 0.294 | 0.383 | 0.027 | 0.038 | 990.599 | 0.328 | 0.666 |
| 3 | (200,100) | 0.360 | 0.432 | 63.837 | 0.312 | 0.429 | 0.003 | 0.002 | 999.000 | 0.849 | 0.150 |

I chose a bigger beta in order to overcome the bias issue.

Table 3. Simulation Result 2

| | | iid5 beta =5 | | | | | iid10 beta =5 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Model | X.p.n. | lenght | cov1 | fn | biais1 | biais2 | lenght2 | cov1.1 | fn2 | biais1.1 | biais2.1 |
| 1 | (50,100) | 0.423 | 0.287 | 0.000 | 0.279 | 0.313 | 0.474 | 0.421 | 0.000 | 0.263 | 0.320 |
| 2 | (100,100) | 0.460 | 0.212 | 0.000 | 0.331 | 0.396 | 0.708 | 0.356 | 10.837 | 0.356 | 0.533 |
| 3 | (200,100) | 0.499 | 0.162 | 0.285 | 0.376 | 0.481 | 1.887 | 0.586 | 241.878 | 0.450 | 1.536 |

Then we compute the method used by lahiri (On the residual empirical process based on the ALASSO in high dimensions and its functional oracle property). In this paper, Lahiri uses the ALASSO estimator and shows that the empirical distribution of estimated residual behaves approximately as a gaussian noise. He then deduces a confidence band of prediction of the variable of interest (y) based on the empirical distribution of the residual.

*Date*: August 7, 2015.

Table 4. Simulation Result

| | | beta=5 iid5 n=400 | | | | | AR(3) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Model | X.p.n. | lenght | cov1 | fn | biais1 | biais2 | lenght2 | cov1.1 | fn2 | biais1.1 | biais2.1 |
| 1 | (50,100) | 0.179 | 0.260 | 0.000 | 0.125 | 0.132 | 0.005 | 0.000 | 200.000 | 1.615 | 0.002 |
| 2 | (100,100) | 0.182 | 0.166 | 0.000 | 0.145 | 0.151 | 0.004 | 0.000 | 200.000 | 1.614 | 0.001 |
| 3 | (200,100) | 0.183 | 0.111 | 0.000 | 0.161 | 0.170 | 0.004 | 0.000 | 200.000 | 1.614 | 0.001 |

Table 5. Simulation Result

| | | iid1 | | iid5 | | AR | |
|---|---|---|---|---|---|---|---|
| Model | X.pn. | coverage | lenght | coverage.1 | lenght.1 | coverage.2 | lenght.2 |
| 1 | (10,100) | 0.859 | 3.368 | 0.877 | 3.436 | 0.877 | 3.437 |
| 2 | (50,100) | 0.932 | 3.654 | 0.761 | 2.982 | 1.000 | 4.073 |
| 3 | (120,100) | 0.934 | 3.825 | 0.970 | 3.956 | 0.893 | 3.501 |
| 4 | (200,100) | 0.748 | 2.933 | 0.930 | 3.868 | 0.988 | 3.982 |