BOOTSTRAP RESULTS

CLMENT CARRIER

Bootstrap

```r
library(knitr)
library(glmnet)
library(MASS)
library(xtable)
require(ggplot2)
```

```r
source('../../laurent/lasso.R')
source('../../Functions/RW.R')
source('../../Functions/fun.R')
source('../../Functions/lahiri.R')
source('../../Functions/lahiriboot.R')
source('../../Functions/lahiriboot2.R')
source('../../Functions/AR1.R')
source('../../Functions/edfAR1.R')
source('../../Functions/edfiid4.R')
source('../../Functions/edfiid1.R')
source('../../Functions/iid1.R')
source('../../Functions/iid5.R')
source('../../Functions/iid10.R')
```

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

		iid								AR							
Model	X.p.n.	lenght	cov1	cov1.1	cov1.2	cov1.3	fn	biais1	biais2	lenght2	cov2	cov2.1	cov2.2	cov2.3	fn2	biais1.1	biais2.1
1	(10,100)	0.138	1.000	0.000	0.000	0.000	0.000	0.436	-0.092	0.255	1.000	0.400	1.000	0.000	0.000	0.217	-0.015
2	(50,100)	0.365	0.900	0.100	1.000	0.000	0.000	0.276	0.031	0.223	1.000	0.800	1.000	0.000	0.000	0.171	-0.021
3	(120,100)	0.273	0.900	0.600	1.000	0.000	0.000	0.171	0.029	0.155	1.000	1.000	1.000	1.000	0.000	0.083	-0.003
4	(200,100)	0.444	0.700	0.300	1.000	0.000	0.000	0.243	0.082	0.202	1.000	1.000	1.000	1.000	0.000	0.041	0.021

In the following one, we increase the number of nonzero parameter.

```
## Error in ystar[, i] <- prediction + estar[, i]:  l'argument de remplacement
est de longueur nulle
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```

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,

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TABLE 2. Simulation Result

		iid 5								iid 10							
Model	X.p.n.	lenght	cov1	cov1.1	cov1.2	cov1.3	fn	biais1	biais2	lenght2	cov2	cov2.1	cov2.2	cov2.3	fn2	biais1.1	biais2.1
1	(10,100)	0.354	0.800	0.780	1.000	1.000	0.000	0.056	-0.083	0.247	0.980	0.820	1.000	0.700	0.000	0.021	-0.003
2	(50,100)	0.341	0.820	0.280	1.000	0.200	0.000	0.220	0.070	0.223	1.000	0.800	1.000	0.000	0.000	0.171	-0.021
3	(120,100)	0.743	0.540	0.200	0.800	0.200	20.000	0.350	0.266	0.155	1.000	1.000	1.000	1.000	0.000	0.083	-0.003
4	(200,100)	0.213	0.820	0.100	1.000	0.200	44.000	0.886	0.004	0.202	1.000	1.000	1.000	1.000	0.000	0.041	0.021

TABLE 3. Simulation Result

iid5		post		nonpost	
Model	X.pn.	coverage	lenght	coverage.1	lenght.1
1	(10,100)	0.643	0.260	0.386	0.371
2	(50,100)	0.718	0.365	0.149	0.289
3	(120,100)	0.915	0.473	0.000	0.389
4	(200,100)	0.844	0.629	0.057	0.348

TABLE 4. Simulation Result

		AR1 (0.7)		AR1 (1)	
Model	X.p.n.	coverage	lenght	coverage.1	lenght.1
1	(10,100)	0.389	0.152	0.349	0.137
2	(50,100)	1.000	0.533	0.475	0.186
3	(120,100)	0.556	0.302	0.239	0.094
4	(200,100)	0.693	0.272	0.650	0.255

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.

TABLE 5. Simulation Result

		iid1		iid5		AR	
Model	X.pn.	coverage	lenght	coverage.1	lenght.1	coverage.2	lenght.2
1	(10,100)	0.939	3.824	0.921	3.796	0.910	3.676
2	(50,100)	0.915	3.604	0.929	3.754	0.940	3.812
3	(120,100)	0.888	3.536	0.953	3.919	0.941	3.803
4	(200,100)	0.917	3.780	0.969	4.376	0.933	3.892