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: increasing n, varying scale of beta.

iid1		beta=1					beta=10				
Model	X.p.n.	lenght	cov1	fn	biais1	biais2	lenght2	cov1.1	fn2	biais1.1	biais2.1
1	(10,100)	0.377	0.910	1.760	0.175	0.189	0.377	0.910	0.000	0.192	0.198
2	(10,500)	0.162	0.900	0.000	0.087	0.084	0.159	0.930	0.000	0.087	0.087
3	(10,1000)	0.117	0.930	0.000	0.057	0.061	0.107	0.860	0.000	0.072	0.070

Table 2. 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)	0.418	0.870	30.290	0.263	0.321	0.263	0.750	3.660	0.218	0.161
2	(100,100)	0.384	0.840	53.060	0.299	0.397	0.277	0.840	9.230	0.260	0.195
3	(200,100)	0.324	0.770	66.190	0.324	0.426	0.256	0.740	20.330	0.293	0.218

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

```
## Error in base::rowMeans(x, na.rm = na.rm, dims = dims, ...):  'x' must be
numeric
## Error in base::rowMeans(x, na.rm = na.rm, dims = dims, ...):  'x' must be
numeric
## Error in base::rowMeans(x, na.rm = na.rm, dims = dims, ...):  'x' must be
numeric
```

Table 3. 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)	0.424	0.536	267.400	0.277	0.473	0.209	0.289	925.180	0.241	0.711
2	(100,100)	0.384	0.310	53.060	0.299	0.397	0.277	0.050	9.230	0.260	0.195
3	(200,100)	0.324	0.400	66.190	0.324	0.426	0.003	0.002	999.000	0.849	0.150

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

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 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

Table 5. 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 6. Simulation Result

		iid1		iid5		AR	
Model	X.pn.	coverage	lenght	coverage.1	lenght.1	coverage.2	lenght.2
1	(10,100)	0.925	3.626	0.834	3.270	0.863	3.383
2	(50,100)	0.932	3.655	0.929	3.642	0.956	3.867
3	(120,100)	0.873	3.423	1.000	4.245	0.810	3.176
4	(200,100)	0.926	3.629	0.925	3.747	1.000	4.409