## Corollary 6.1 in Bühlmann and van de Geer (2011)

 Corollary 6.1 assume:- $\varepsilon \sim \mathcal{N}_{n}\left(0, \sigma^{2} I\right)$
- scaled columns $\hat{\sigma}_{j}^{2} \equiv 1 \forall j$

For

$$
\lambda=4 \hat{\sigma} \sqrt{\frac{t^{2}+2 \log (p)}{n}}
$$

where $\hat{\sigma}$ is an estimator for $\sigma$. Then, with probability at least $1-\alpha$ where

$$
\alpha=2 \exp \left(-t^{2} / 2\right)+\mathbb{P}[\hat{\sigma}<\sigma]
$$

we have that

$$
\left\|X\left(\hat{\beta}-\beta^{0}\right)\right\|_{2}^{2} / n \leq \frac{3}{2} \lambda\left\|\beta^{0}\right\|_{1}
$$

## Implications

Corollary 6.1 implies:

$$
\left\|X\left(\hat{\beta}-\beta^{0}\right)\right\|_{2}^{2} / n=O_{P}(\underbrace{\lambda}_{\asymp \sqrt{\log (p) / n}}\left\|\beta^{0}\right\|_{1})=O_{P}\left(\sqrt{\log (p) / n}\left\|\beta^{0}\right\|_{1}\right)
$$

even for very sparse case with $\left\|\beta^{0}\right\|_{1}=O(1)$ :
slow convergence rate of order $O_{P}(\sqrt{\log (p) / n})$
benchmark: OLS orcale on the variables from $S_{0}=\left\{j ; \beta_{j}^{0} \neq 0\right\}$

$$
\left\|X\left(\hat{\beta}_{\text {OLS-oracle }}-\beta^{0}\right)\right\|_{2}^{2} / n=O_{P}\left(s_{0} / n\right), \quad s_{0}=\left|S_{0}\right|
$$

we will later derive for the Lasso, under additional assumptions on $X$ : fast convergence rate

$$
\left\|X\left(\hat{\beta}-\beta^{0}\right)\right\|_{2}^{2} / n=O_{P}\left(\log (p) \frac{S_{0}}{n}\right)
$$

for slow rate: no assumptions on $X$ (could have perfectly correlated columns)

## Extensions

the proof technique decouples into a deterministic and probablistic part (the set $\mathcal{T}$ )
the deterministic part remains the same for other probabilistic structures (other analysis for $\mathbb{P}[\mathcal{T}]$ ) such as:

- heteroscedastic errors with

$$
\mathbb{E}\left[\varepsilon_{i}\right]=0, \operatorname{Var}\left(\varepsilon_{i}\right)=\sigma_{i}^{2} \not \equiv \text { const. }
$$

- dependent observations $\leadsto$ for fixed design, dependent errors
- non-Gaussian errors
sub-Gaussian distribution
second moments plus bounded $X$ : see Example 14.3 in Bühlmann and van de Geer (2011)
- random design: assume that $\varepsilon$ is independent of $X$
$\leadsto$ condition on $X$ : invoke the results for fixed design and integrate out
heteroscedastic errors
$\varepsilon \sim \mathcal{N}_{n}(0, D)$, where $D=\operatorname{diag}\left(\sigma_{1}^{2}, \ldots, \sigma_{n}^{2}\right)$
assume that: $\quad \sigma_{i}^{2} \leq \underbrace{\sigma^{2}}_{\text {some pos. const. }}<\infty$

Then, Coroallry 6.1 remains true with $\sigma^{2}$ as above
Proof:
exactly as before but exploiting that $V_{j} \sim \mathcal{N}\left(0, \tau_{j}^{2}\right)$ with $\tau_{j} \leq 1$ and using that $\mathbb{P}\left[\left|V_{j}\right|>c\right] \leq \mathbb{P}[\underbrace{|Z|}_{\sim|\mathcal{N}(0,1)|}>c]$

Exercise: work out the details.
errors from stationary distribution
$\varepsilon \sim \mathcal{N}_{n}(0, \Gamma)$, where $\Gamma_{i, j}=R(i-j)=R(j-i)$
assume that: $\quad \sum_{k=-\infty}^{\infty}|R(k)|<\infty$ and $\left|X_{i}^{(j)}\right| \leq K_{X}<\infty$
Then, Corollary 6.1 remains true with $\sigma^{2}=K_{X}^{2} \sum_{k=-\infty}^{\infty}|R(k)|$
Proof:
Exercise. (A bit more tricky...)

