

# Recap

## Inference in high-dimensional linear models: p-values and confidence intervals

one cannot use the bootstrap or subsampling for approximating the distribution of the Lasso

it is inconsistent due to non-Gaussian limiting distribution of the Lasso

if  $a_n(\hat{\beta}_{\text{Lasso};j} - \beta_j^0) \implies Z, Z \sim \text{non-Gaussian distribution } F$   
then  $a_n(\underbrace{\hat{\beta}_{\text{Lasso};j}^*}_{\text{bootstrapped}} - \hat{\beta}_{\text{Lasso};j}) \not\implies Z \text{ in probability}$

## De-biased or De-sparsified Lasso

consider (as in partialing-out):

$$Z^{(j)} = X^{(j)} - X^{(-j)}\hat{\gamma}^{(j)}$$

= Lasso residuals from  $X^{(j)}$  vs.  $X^{(-j)} = \{X^{(k)}; k \neq j\}$

$$\hat{\gamma}^{(j)} = \operatorname{argmin}_{\gamma} \|X^{(j)} - X^{(-j)}\gamma\|_2^2 + \lambda_j \|\gamma\|_1$$

build projection of  $Y$  onto  $Z^{(j)}$ :

$$\frac{Y^T Z^{(j)}}{(X^{(j)})^T Z^{(j)}} \underbrace{=}_{Y=X\beta^0+\varepsilon} \beta_j^0 + \underbrace{\sum_{k \neq j} \frac{(X^{(k)})^T Z^{(j)}}{(X^{(j)})^T Z^{(j)}} \beta_k^0}_{\text{bias}} + \frac{\varepsilon^T Z^{(j)}}{(X^{(j)})^T Z^{(j)}}$$

estimate bias and subtract it:

$$\widehat{\text{bias}} = \sum_{k \neq j} \frac{(X^{(k)})^T X^{(j)}}{(X^{(j)})^T Z^{(j)}} \underbrace{\hat{\beta}_k}_{\text{standard Lasso}}$$

→ de-biased/de-sparsified Lasso estimator

$$\hat{b}_j = \frac{Y^T Z^{(j)}}{(X^{(j)})^T Z^{(j)}} - \sum_{k \neq j} \frac{(X^{(k)})^T Z^{(j)}}{(X^{(j)})^T Z^{(j)}} \hat{\beta}_k \quad (j = 1, \dots, p)$$

**not sparse!** Never equal to zero for all  $j = 1, \dots, p$

computation: for computing all  $\hat{b}_j$ ,  $j = 1, \dots, p$

→  $p + 1$  Lasso fits

i.e.  $O(p \underbrace{np \min(n, p)}_{\text{comp. Compl. of Lasso}}) = O(p^2 n^2)$  comp. complexity

comp. Compl. of Lasso

if  $p \gg n$

*Theorem 10.1 in the notes*

assume:

- ▶  $\varepsilon \sim \mathcal{N}(0, \sigma^2 I)$
- ▶  $\lambda_j = C_j \sqrt{\log(p)/n}$  and  $\|Z^{(j)}\|_2^2/n \geq L > 0$
- ▶  $s_0 = o(\sqrt{n}/\log(p))$  (a bit more sparse than “usual”)
- ▶  $\|\hat{\beta} - \beta^0\|_1 = O_P(s_0 \sqrt{\log(p)/n})$   
(i.e., compatibility constant  $\phi_0^2$  bounded away from zero)

Then:

$$\sigma^{-1} \sqrt{n} \frac{(X^{(j)})^T Z^{(j)}/n}{\|Z^{(j)}\|_2/\sqrt{n}} (\hat{b}_j - \beta_j^0) \implies \mathcal{N}(0, 1) \quad (j = 1, \dots, p)$$

plugging-in  $\hat{\sigma}$ :  $\rightsquigarrow$  confidence intervals/hypothesis testing for  $\beta_j^0$