

Recap

Group Lasso (Yuan and Lin, 2006)

groups $\mathcal{G}_1, \dots, \mathcal{G}_q$ which build a partition of $\{1, \dots, p\}$
write the (high-dimensional) parameter vector as

$$\beta = (\beta_{\mathcal{G}_1}, \beta_{\mathcal{G}_2}, \dots, \beta_{\mathcal{G}_q})^T$$

goal: an estimator which is “group-sparse”, i.e.:
for all $j = 1, \dots, p$,

either $\hat{\beta}_{\mathcal{G}_j} \equiv 0$

or $(\hat{\beta}_{\mathcal{G}_j})_r \neq 0 \forall r \in \mathcal{G}_j$

prime example: factor covariates which are encoded by a certain “dummy encoding”

→ group sparsity then correspond to sparsity in main effects and interaction terms of factor variables

Group Lasso:

$$\hat{\beta}(\lambda) = \operatorname{argmin}_{\beta} \left(\|Y - X\beta\|_2^2/n + \lambda \sum_{j=1}^q m_j \|\beta_{\mathcal{G}_j}\|_2 \right)$$

where typically $m_j = \sqrt{|\mathcal{G}_j|}$

group sparsity because objective function is non-differentiable at $\|\beta_{\mathcal{G}_j}\|_2 = 0 \iff \beta_{\mathcal{G}_j} \equiv 0 \ (j = 1, \dots, q)$

The generalized Group Lasso penalty

$$\text{pen}(\beta) = \lambda \sum_{j=1}^q m_j \sqrt{\beta_{\mathcal{G}_j}^T \mathbf{A}_j \beta_{\mathcal{G}_j}}, \quad \mathbf{A}_j \text{ positive definite}$$

important example: **groupwise prediction penalty**

$$\text{pen}(\beta) = \sum_{j=1}^q m_j \|\mathbf{X}_{\mathcal{G}_j} \beta_{\mathcal{G}_j}\|_2 = \lambda \sum_{j=1}^q m_j \sqrt{\beta_{\mathcal{G}_j}^T \mathbf{X}_{\mathcal{G}_j}^T \mathbf{X}_{\mathcal{G}_j} \beta_{\mathcal{G}_j}}$$

$\mathbf{X}_{\mathcal{G}_j}^T \mathbf{X}_{\mathcal{G}_j}$ typically positive definite for $|\mathcal{G}_j| < n$

- ▶ penalty is **invariant** under arbitrary reparameterizations within every group \mathcal{G}_j : important!
- ▶ when using an orthogonal parameterization such that $\mathbf{X}_{\mathcal{G}_j}^T \mathbf{X}_{\mathcal{G}_j} = \mathbf{I}$: it is the standard Group Lasso

High-dimensional additive models

$$Y_i = \mu + \sum_{j=1}^p f_j(X_i^{(j)}) + \varepsilon_i \quad (i = 1, \dots, n; p \gg n)$$

$$f_j : \mathbb{R} \rightarrow \mathbb{R} \text{ smooth, } \mathbb{E}[f_j(X_i^{(j)})] \equiv 0 \quad \forall j$$

aim: estimator such that either $\hat{f}_j(\cdot) \equiv 0$ or $\hat{f}_j(\cdot)$ is not the zero function

→ Group Lasso type problem

for $p < n$: regularize w.r.t. smoothness

for $p \gg n$: need to additionally regularize w.r.t. sparsity