

Topic 13: Non-convex Learning + Lasso

by Sai Zhang

Key points: Combining the best of the two, we can use **Lasso plus Concave** method, with Lasso screening and concave component selecting variables, achieving a coordinated intrinsic two-scale learning.

Disclaimer: The note is built on Prof. *Jinchi Lv*'s lectures of the course at USC, DSO 607, High-Dimensional Statistics and Big Data Problems.

We are facing a tradeoff:

- **Convex** methods: have appealing prediction power and oracle inequalities, but challenging to provide tight false sign rate control
- **Concave** methods: have good variable selection properties, but challenging to establish global properties and risk properties

Here, we take advantage of the linearity of Lasso (convex *and* concave) and try to combine it with concave regularization to get the best of both.

13.1 Model Setup

Again, consider a linear regression model $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$, where

- response vector ($n \times 1$): $\mathbf{y} = (y_1, \dots, y_n)'$
- design matrix ($n \times p$): $\mathbf{X} = (\mathbf{x}_1, \dots, \mathbf{x}_p)$, with each column rescaled to have L_2 -norm $n^{1/2}$

here, we consider a scenario where

- $\boldsymbol{\beta}_0 = (\beta_{0,1}, \dots, \beta_{0,p})'$ is *sparse* (with many 0 components)
- ultra-high dimensions: $\log p = O(n^a)$, for some $0 < a < 1$

and consider the penalized least squares

$$\min_{\boldsymbol{\beta} \in \mathbb{R}^p} \left\{ (2n)^{-1} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 + \lambda_0 \|\boldsymbol{\beta}\|_1 + \|p_\lambda(\boldsymbol{\beta})\|_1 \right\} \quad (13.1)$$

where

- $\lambda_0 = c \left(\frac{\log p}{n} \right)^{1/2}$ for some $c > 0$
- $p_\lambda(\boldsymbol{\beta}) = p_\lambda(|\boldsymbol{\beta}|) = (p_\lambda(|\beta_1|), \dots, p_\lambda(|\beta_p|))'$, with $|\boldsymbol{\beta}| = (|\beta_1|, \dots, |\beta_p|)'$; the concave penalty $p_\lambda(t)$ is defined on $t \in [0, \infty)$, indexed by $\lambda \geq 0$, increasing in both t and λ , $p_\lambda(0) = 0$

the 2 penalty components

- L_1 -component: minimum amount of regularization for removing noise in prediction
- concave component $\|p_\lambda(\boldsymbol{\beta})\|_1$: adapt model sparsity for variable selection

Under this set up, we can derive the hard-thresholding property as

Proposition 13.1.1: Hard-Thresholding Property

Assume the $p_\lambda(t)$, $t \geq 0$, is **increasing and concave** with

- $p_\lambda(t) \geq p_{H,\lambda}(t) = \frac{1}{2} [\lambda^2 - (\lambda - t)_+^2]$ on $[0, \lambda]$
- $p'_\lambda((1 - c_1)\lambda) \leq c_1\lambda$ for some $c_1 \in [0, 1)$
- $-p''_\lambda(t)$ decreasing on $[0, (1 - c_1)\lambda]$

then any local minimizer of 13.1 that is also a global minimizer in each coordinate has the **hard-thresholding** feature that each component is either 0 or of magnitude **larger** than $(1 - c_1)\lambda$

Such property is shared by a wide class of concave penalties, including hard-thresholding penalty $p_{H,\lambda}(t)$ with $c_1 = 0$, L_0 -penalty, and SICA (with suitable c_1).

How to understand this proposition? Let $\hat{\beta} = (\hat{\beta}_1, \dots, \hat{\beta}_p)'$

With the hard-thresholding property of Prop. 13.1.1, we can prove a basic constraint for the global optimum $\hat{\beta}$ on an event with significant probability (Fan and Lv, 2014)

$$\|\delta_2\|_1 \leq 7\|\delta_1\|_1$$

where $\delta = \hat{\beta} - \beta_0 = (\delta'_1, \delta'_2)'$, with $\delta_1 \in \mathbb{R}^s$.

References

Yingying Fan and Jinchi Lv. Asymptotic properties for combined l_1 and concave regularization. *Biometrika*, 101(1):57–70, 2014.