Erratum to The Strong Screening Rule for SLOPE

Johan Larsson

Dept. of Statistics, Lund University johan.larsson@stat.lu.se

Małgorzata Bogdan

Dept. of Mathematics, University of Wroclaw Dept. of Statistics, Lund University malgorzata.bogdan@uwr.edu.pl

Jonas Wallin

Dept. of Statistics, Lund University jonas.wallin@stat.lu.se

This file contains an erratum for Larsson et al. [1]. In Theorem 1 in the paper we left out a condition for the subdifferential of the SLOPE penalty, namely that $\operatorname{sign} \beta_{\mathcal{A}_i} = \operatorname{sign} s$. The updated and corrected theorem is given in Theorem 1. Note that the condition was in fact included in the proof of the theorem, which therefore requires no changes.

Theorem 1. The subdifferential $\partial J(\beta; \lambda) \in \mathbb{R}^p$ is the set of all $g \in \mathbb{R}^p$ such that

$$g_{\mathcal{A}_{i}} = \left\{ s \in \mathbb{R}^{\operatorname{card} \mathcal{A}_{i}} \mid \begin{cases} \operatorname{cumsum}(|s|_{\downarrow} - \lambda_{R(s)_{\mathcal{A}_{i}}}) \leq \mathbf{0} & \text{if } \beta_{\mathcal{A}_{i}} = \mathbf{0}, \\ \operatorname{cumsum}(|s|_{\downarrow} - \lambda_{R(s)_{\mathcal{A}_{i}}}) \leq \mathbf{0} & \\ \wedge \sum_{j \in \mathcal{A}_{i}} \left(|s_{j}| - \lambda_{R(s)_{j}}\right) = 0 & \\ \wedge \operatorname{sign} \beta_{\mathcal{A}_{i}} = \operatorname{sign} s & \text{otherwise.} \end{cases} \right\}$$

References

[1] Johan Larsson, Małgorzata Bogdan, and Jonas Wallin. The strong screening rule for SLOPE. In Hugo Larochelle, Marc'Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin, editors, *Advances in Neural Information Processing Systems 33*, volume 33, pages 14592–14603. Curran Associates, Inc. ISBN 978-1-71382-954-6. URL https://papers.nips.cc/paper%5Ffiles/paper/2020/hash/a7d8ae4569120b5bec12e7b6e9648b86-Abstract.html.