

Computation & optimization for Lasso - part 2

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Overview

1. Coordinate Descent
2. A Simulation Study
3. Least Angle Regression
4. ADMM
5. Min-Max Algorithms
6. Alternating Minimizations
7. Screening Rules

Alternating Direction Method of Multipliers (ADMM)

Problem

$$\underset{\beta \in \mathbb{R}^m, \theta \in \mathbb{R}^n}{\text{minimize}} \ f(\beta) + g(\theta) \quad \text{subject to} \ \mathbf{A}\beta + \mathbf{B}\theta = c$$

Augmented Lagrangian

$$L_{\rho}(\beta, \theta, \mu) := f(\beta) + g(\theta) + \langle \mu, \mathbf{A}\beta + \mathbf{B}\theta - c \rangle + \frac{\rho}{2} \|\mathbf{A}\beta + \mathbf{B}\theta - c\|_2^2$$

Dual variable update

$$\beta^{t+1} = \arg \min_{\beta \in \mathbb{R}^m} L_{\rho}(\beta, \theta^t, \mu^t)$$

$$\theta^{t+1} = \arg \min_{\theta \in \mathbb{R}^m} L_{\rho}(\beta^{t+1}, \theta, \mu^t)$$

$$\mu^{t+1} = \mu^t + \rho(\mathbf{A}\beta^{t+1} + \mathbf{B}\theta^{t+1} - c)$$

ADMM for the Lasso

Problem in Lagrangian form

$$\underset{\beta \in \mathbb{R}^p, \theta \in \mathbb{R}^p}{\text{minimize}} \left\{ \frac{1}{2} \|\mathbf{y} - \mathbf{X}\beta\|_2^2 + \lambda \|\theta\|_1 \right\} \quad \text{such that } \beta - \theta = 0$$

Update

$$\beta^{t+1} = (\mathbf{X}^T \mathbf{X} + \rho \mathbf{I})^{-1} (\mathbf{X}^T \mathbf{y} + \rho \theta^t - \mu^t)$$

$$\theta^{t+1} = \mathcal{S}_{\lambda/\rho}(\beta^{t+1} + \mu^t/\rho)$$

$$\mu^{t+1} = \mu^t + \rho(\beta^{t+1} - \theta^{t+1})$$

where $\mathcal{S}_{\lambda/\rho}(z) = \text{sign}(z)(|z| - \frac{\lambda}{\rho})_+$.

Dual Polytope Projection (DPP)

Suppose we want to calculate a lasso solution at $\lambda < \lambda_{\max}$.
The DPP rule discards the j^{th} variable if

$$\left| \mathbf{x}_j^T \mathbf{y} \right| < \lambda_{\max} - \|\mathbf{x}_j\|_2 \|\mathbf{y}\|_2 \frac{\lambda_{\max} - \lambda}{\lambda}$$

Sequential DPP rule

Suppose we have the lasso solution $\hat{\beta}(\lambda')$ at λ' and want to
screen variables for solutions at $\lambda < \lambda'$. We discard the j^{th}
variable if

$$\left| \mathbf{x}_j^T (\mathbf{y} - \mathbf{X} \hat{\beta}(\lambda')) \right| < \lambda' - \|\mathbf{x}_j\|_2 \|\mathbf{y}\|_2 \frac{\lambda_{\max} - \lambda}{\lambda}$$

Global Strong Rule

Suppose we want to calculate a lasso solution at $\lambda < \lambda_{\max}$. The global strong rule discards the j^{th} variable if

$$\left| \mathbf{x}_j^T \mathbf{y} \right| < \lambda - (\lambda_{\max} - \lambda) = 2\lambda - \lambda_{\max}$$

Sequential Strong Rule

Suppose we have the lasso solution $\hat{\beta}(\lambda')$ at λ' and want to screen variables for solutions at $\lambda < \lambda'$. We discard the j^{th} variable if

$$\left| \mathbf{x}_j^T (\mathbf{y} - \mathbf{X} \hat{\beta}(\lambda')) \right| < 2\lambda - \lambda'$$

Paragraphs of Text

Sed iaculis dapibus gravida. Morbi sed tortor erat, nec interdum arcu. Sed id lorem lectus. Quisque viverra augue id sem ornare non aliquam nibh tristique. Aenean in ligula nisl. Nulla sed tellus ipsum. Donec vestibulum ligula non lorem vulputate fermentum accumsan neque mollis.

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Bullet Points

- Lorem ipsum dolor sit amet, consectetur adipiscing elit
- Aliquam blandit faucibus nisi, sit amet dapibus enim tempus eu
- Nulla commodo, erat quis gravida posuere, elit lacus lobortis est, quis porttitor odio mauris at libero
- Nam cursus est eget velit posuere pellentesque
- Vestibulum faucibus velit a augue condimentum quis convallis nulla gravida

Blocks of Highlighted Text

Block 1

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Block 2

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Block 3

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Multiple Columns

Heading

- 1 Statement
- 2 Explanation
- 3 Example

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Treatments	Response 1	Response 2
Treatment 1	0.0003262	0.562
Treatment 2	0.0015681	0.910
Treatment 3	0.0009271	0.296

Table: Table caption

Theorem

Theorem (Mass–energy equivalence)

$$E = mc^2$$

Example (Theorem Slide Code)

```
\begin{frame}  
\frametitle{Theorem}  
\begin{theorem}[Mass--energy equivalence]  
$E = mc^2$  
\end{theorem}  
\end{frame}
```

Figure

Uncomment the code on this slide to include your own image from the same directory as the template .TeX file.

Citation

An example of the `\cite` command to cite within the presentation:

This statement requires citation [Hastie et al., 2015].

References



Trevor Hastie, Robert Tibshirani, and Martin Wainwright (2015)
Statistical learning with sparsity: the Lasso and generalizations
CRC Press; Boca Raton, FL

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The End