Notes on Approximate Leave-One-Out for Elastic Net

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1 ALO for Elastic Net, Approximation in the Primal Domain

Recall the objective function for the elastic net problem:

$$\min_{\boldsymbol{\beta}} \frac{1}{2}\sum_{j=1}^{n}(\boldsymbol{x}_j^\top \boldsymbol{\beta} - y_j)^2 + \lambda\left(\alpha\|\boldsymbol{\beta}\|_1 + \frac{1-\alpha}{2}\|\boldsymbol{\beta}\|_2^2\right).$$

Let $A = \{i : \beta_i \notin K, i = 1, \dots, p\}$ be the active set, we have

$$\dot{\ell}(\boldsymbol{x}_j^\top \boldsymbol{\beta};\, y_j) = \boldsymbol{x}_j^\top \boldsymbol{\beta} - y_j, \qquad \ddot{\ell}(\boldsymbol{x}_j^\top \boldsymbol{\beta};\, y_j) = 1, \qquad \nabla^2 R(\hat{\boldsymbol{\beta}}_A) = (1-\alpha)\lambda \boldsymbol{I}_{A,A}.$$

Thus, Eqn. 31 reduces to

$$\boldsymbol{H} = \boldsymbol{X}_{\cdot,A}\left[\boldsymbol{X}_{\cdot,A}^\top \boldsymbol{X}_{\cdot,A} + (1-\alpha)\,\lambda \boldsymbol{I}_{A,A}\right]^{-1}\boldsymbol{X}_{\cdot,A}^\top.$$

By augmenting $\boldsymbol{X}$ with an extra column of 1s, adding the intercept back to the model is straightforward, as Eqn. 31 now becomes

$$\boldsymbol{H} = [\boldsymbol{1}_n, \boldsymbol{X}_{\cdot,A}]\left\{[\boldsymbol{1}_n, \boldsymbol{X}_{\cdot,A}]^\top \boldsymbol{D}\,[\boldsymbol{1}_n, \boldsymbol{X}_{\cdot,A}] + \nabla^2 R\left(\hat{\beta}_0, \hat{\boldsymbol{\beta}}_A\right)\right\}^{-1}[\boldsymbol{1}_n, \boldsymbol{X}_{\cdot,A}]^\top,$$

where

$$\boldsymbol{D} = \operatorname{diag}\left[\ddot{\ell}\left(\hat{\beta}_0 + \boldsymbol{x}_j^\top \hat{\boldsymbol{\beta}}; y_j\right)\right]_{j\in A} = \boldsymbol{I}_{A,A}, \qquad \nabla^2 R\left(\hat{\beta}_0, \hat{\boldsymbol{\beta}}_A\right) = \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & (1-\alpha)\lambda & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & (1-\alpha)\lambda \end{bmatrix}.$$

Therefore, the ALO update is

$$\begin{bmatrix} 1 & \boldsymbol{x}_i^\top \end{bmatrix}\begin{bmatrix} \tilde{\beta}_0^{\setminus i} \\ \tilde{\boldsymbol{\beta}}^{\setminus i} \end{bmatrix} = (\hat{\beta}_0 + \boldsymbol{x}_i^\top \hat{\boldsymbol{\beta}}) + \frac{\boldsymbol{H}_{ii}}{1 - \boldsymbol{H}_{ii}\ddot{\ell}\left(\hat{\beta}_0 + \boldsymbol{x}_i^\top \hat{\boldsymbol{\beta}}; y_i\right)}\dot{\ell}\left(\hat{\beta}_0 + \boldsymbol{x}_i^\top \hat{\boldsymbol{\beta}}; y_i\right)$$

2 ALO for Elastic Net, Approximation with Proximal Formulation

For the elastic net problem, the proximal mapping is known to be

$$\mathbf{prox}_R\left(\boldsymbol{z}\right) = \gamma\,\mathrm{sgn}(\boldsymbol{z}) \odot (|\boldsymbol{z}| - \lambda \mathbf{1}_p)_+, \qquad \gamma = \frac{1}{1+(1-\alpha)\lambda}.$$

Let E be the active set, if $z_i \in E$, then

$$\frac{\partial}{\partial z_i}\gamma\,\mathrm{sgn}(z_i)(|z_i| - \lambda)_+ = \gamma.$$

Plug in $\boldsymbol{z} = \hat{\boldsymbol{\beta}} - \sum_{j=1}^n \dot{\ell}(\boldsymbol{x}_j^\top \hat{\boldsymbol{\beta}};\, y_j)\boldsymbol{x}_j$, Eqn. 46 thus reduce to

$$\boldsymbol{H} = \gamma \boldsymbol{X}_{\cdot,E}\left[\gamma \boldsymbol{X}_{\cdot,E}^\top \boldsymbol{X}_{\cdot,E} + \left(1-\gamma\right)\boldsymbol{I}_{E,E}\right]^{-1} \boldsymbol{X}_{\cdot,E}^\top.$$

Bringing back the intercept term is straightforward as well. Noted that

$$\begin{bmatrix}\hat{\beta}_0^{\setminus i}\\ \hat{\boldsymbol{\beta}}^{\setminus i}\end{bmatrix} = \mathbf{prox}_R\left(\boldsymbol{z}\right), \qquad \boldsymbol{z} = \begin{bmatrix}\hat{\beta}_0^{\setminus i}\\ \hat{\boldsymbol{\beta}}^{\setminus i}\end{bmatrix} - \sum_{j\neq i}\begin{bmatrix}1\\ \boldsymbol{x}_j\end{bmatrix}\dot{\ell}\left(\hat{\beta}_0^{\setminus i} + \boldsymbol{x}_j^\top \hat{\boldsymbol{\beta}}^{\setminus i}; y_j\right).$$

Hence, from the first-order condition $\sum_{j\neq i}\dot{\ell}\left(\hat{\beta}_0^{\setminus i} + \boldsymbol{x}_j^\top \hat{\boldsymbol{\beta}}^{\setminus i}; y_j\right) = 0$, we can derive that

$$\boldsymbol{J}_{E,E} = [\boldsymbol{J}(\boldsymbol{u})]_{E,E} = \begin{bmatrix}1 & 0 & 0 & \dots & 0\\ 0 & (1-\alpha)\lambda & 0 & \dots & 0\\ 0 & 0 & (1-\alpha)\lambda & \dots & 0\\ \vdots & \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & 0 & 0 & (1-\alpha)\lambda\end{bmatrix}^{-1}.$$

The ALO formula is then immediate by Thm. 5.1.

3 ALO for LASSO, with Intercept through Generalized LASSO

For the generalized LASSO problem

$$\min_{\boldsymbol{\beta}} \frac{1}{2}||\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta}|| + \lambda||\boldsymbol{D}\beta||_1,$$

the dual problem is derived as:

$$\min_{\boldsymbol{u}} \frac{1}{2}||\boldsymbol{y} - \boldsymbol{\theta}||_2^2, \qquad \theta \in \{\boldsymbol{X}^\top\boldsymbol{\theta} = \boldsymbol{D}^\top bu, ||\boldsymbol{u}||_\infty \leq \lambda\}.$$

The dual problem could be written in a proximal approach, such that:

$$\hat{u} = \mathbf{prox}_R(\boldsymbol{y}), \qquad R(\boldsymbol{u}) = \begin{cases}0 & \boldsymbol{\theta} \in \{\boldsymbol{X}^\top\boldsymbol{\theta} = \boldsymbol{D}^\top\boldsymbol{u}, ||\boldsymbol{u}||_\infty \leq \lambda\},\\ \infty & \text{otherwise.}\end{cases}$$

Denote $\boldsymbol{J}$ as the Jacobian of the proximal operator at the full data problem $\boldsymbol{y}$, then the ALO estimator could be obtained as:

$$\boldsymbol{y}^{\setminus i} = \boldsymbol{y}_i - \frac{\hat{\boldsymbol{u}}_i}{\boldsymbol{J}_{ii}}.$$

For the case of LASSO with an intercept, we could expand the $\boldsymbol{X}$ with a column of ones in the first column, expand $\boldsymbol{\beta}$ with another dimension and choose $\boldsymbol{D} = [\boldsymbol{0}, \boldsymbol{I}]$. Let $E := \{j : |\boldsymbol{X}_j^\top \theta| = \lambda\}$ denote the active set. The Jacobian is locally given as the projection onto the orthogonal complement of the span of $\boldsymbol{X}_E$ and the vector of ones. Further denote $\tilde{\boldsymbol{X}}_E = [\boldsymbol{1}, \boldsymbol{X}_E]$, then the Jacobian is given as $\boldsymbol{I} - \tilde{\boldsymbol{X}}_E(\tilde{\boldsymbol{X}}_E^\top \tilde{\boldsymbol{X}}_E)\tilde{\boldsymbol{X}}_E^\top$.

4 Usage of ALO formulae with `glmnet` package

The `glmnet` package scales the elastic net loss function by a factor of $1/n$, so the ALO formulae must be adjusted accordingly, e.g. for the proximal one, we instead have:

$$\tilde{\boldsymbol{y}}_j^{\setminus i} = \hat{\boldsymbol{y}}_j + \frac{\boldsymbol{H}_{ii}(\hat{\boldsymbol{y}}_j - \boldsymbol{y}_j)}{n - \boldsymbol{H}_{ii}}, \qquad \boldsymbol{H} = \gamma \boldsymbol{X}_{\cdot,E}\left[\frac{\gamma}{n}\boldsymbol{X}_{\cdot,E}^\top \boldsymbol{X}_{\cdot,E} + (1-\gamma)\,\boldsymbol{I}_{E,E}\right]^{-1}\boldsymbol{X}_{\cdot,E}^\top.$$

Furthermore, `glmnet` implicitly "standardizes y to have unit variance before computing its λ sequence (and then unstandardizes the resulting coefficients)". So to get comparable result, it is necessary to rescale $\boldsymbol{y}$ by the MLE $\hat{\sigma}_y$ before fitting the model. Figure 1 shows the comparison of the ALO and LOO for different αs. Without standardizing $\boldsymbol{y}$ first, a growing discrepancy between the two curves can be observed as $\alpha \to 0$.

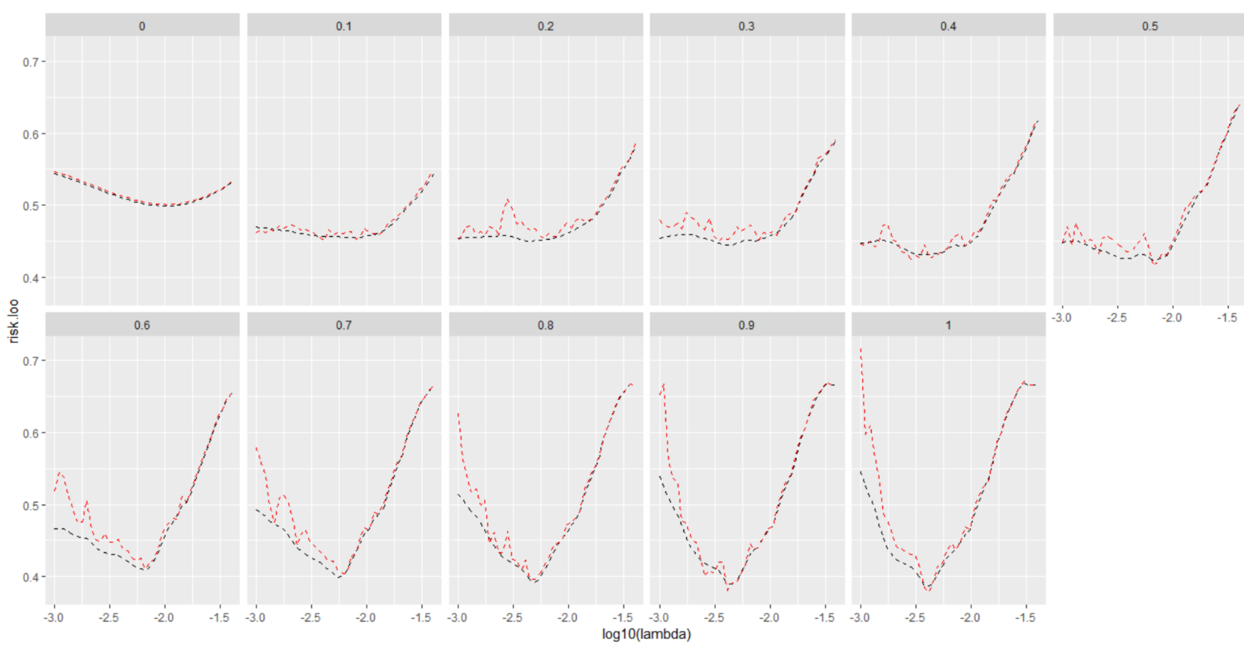

Figure 1: ALO vs. LOO for Elastic Net.