Applied Machine Learning

- Ridge Regularization
- Lasso Regularization
- Elastic Net

Ridge Regularization

Minimization goal includes regularization term

$$\frac{1}{N}(\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^T(\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) + \lambda \boldsymbol{\beta}^T \boldsymbol{\beta}$$

- $\lambda \ge 0$ penalizes large values of β
- L_2 norm: $\|\beta\|_2 = \beta^\top \beta$

•
$$e(\beta_k) = (a + \lambda)\beta_k^2 - 2b(\beta_{-k})\beta_k + c(\beta_{-k})$$
 $\Rightarrow \beta_k = \frac{b(\beta_{-k})}{a + \lambda}$

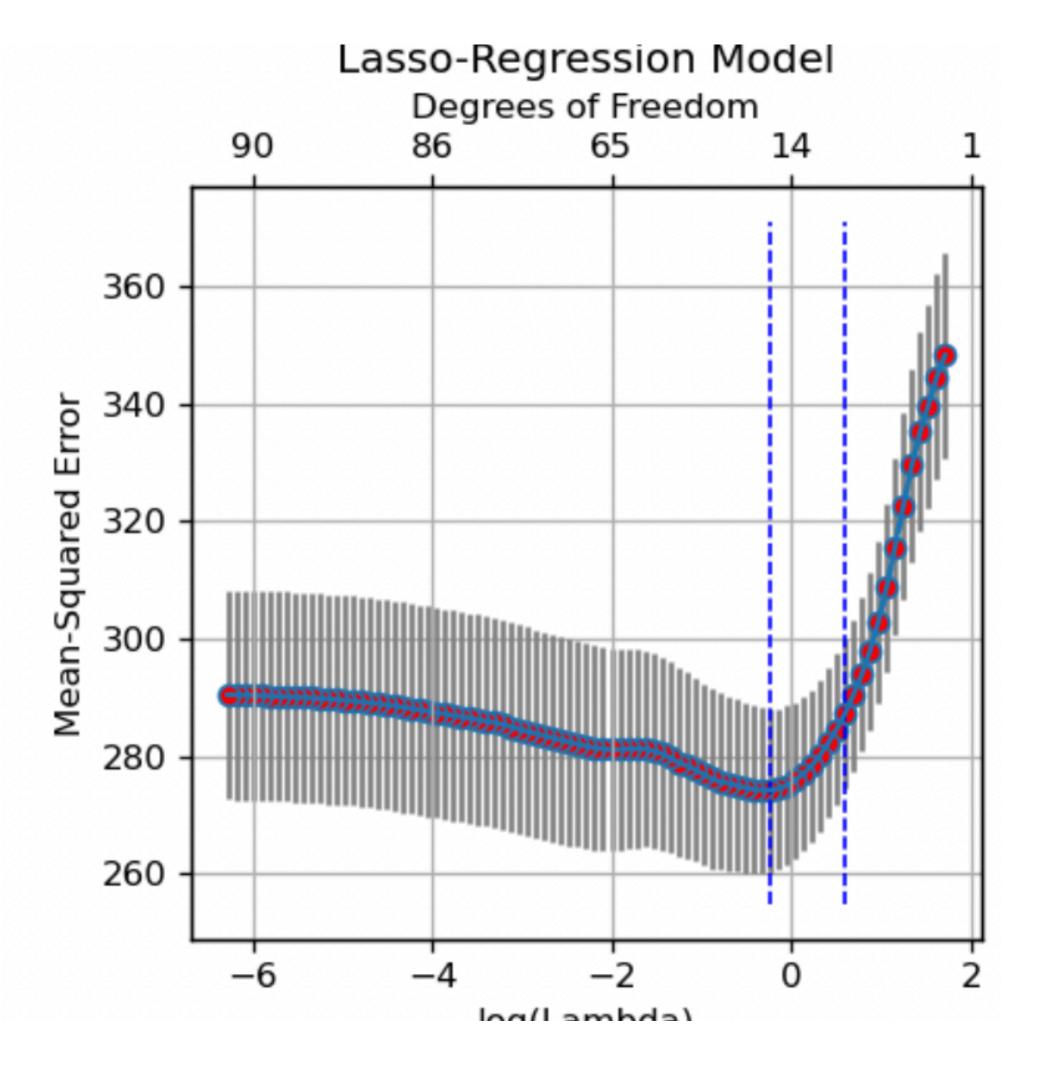
Lasso Regularization

$$L_1 \text{ norm: } \|\beta\|_1 = \sum_k |\beta_k|$$

Minimization Goal:

$$\frac{1}{N}(\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^T(\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) + \lambda \|\boldsymbol{\beta}\|_1$$

- statistic libraries
 - stochastic descent is not a good option
 - solve regularization path for all values of $\lambda > 0$
- Explanatory variables with corresponding coefficient = 0 can be removed



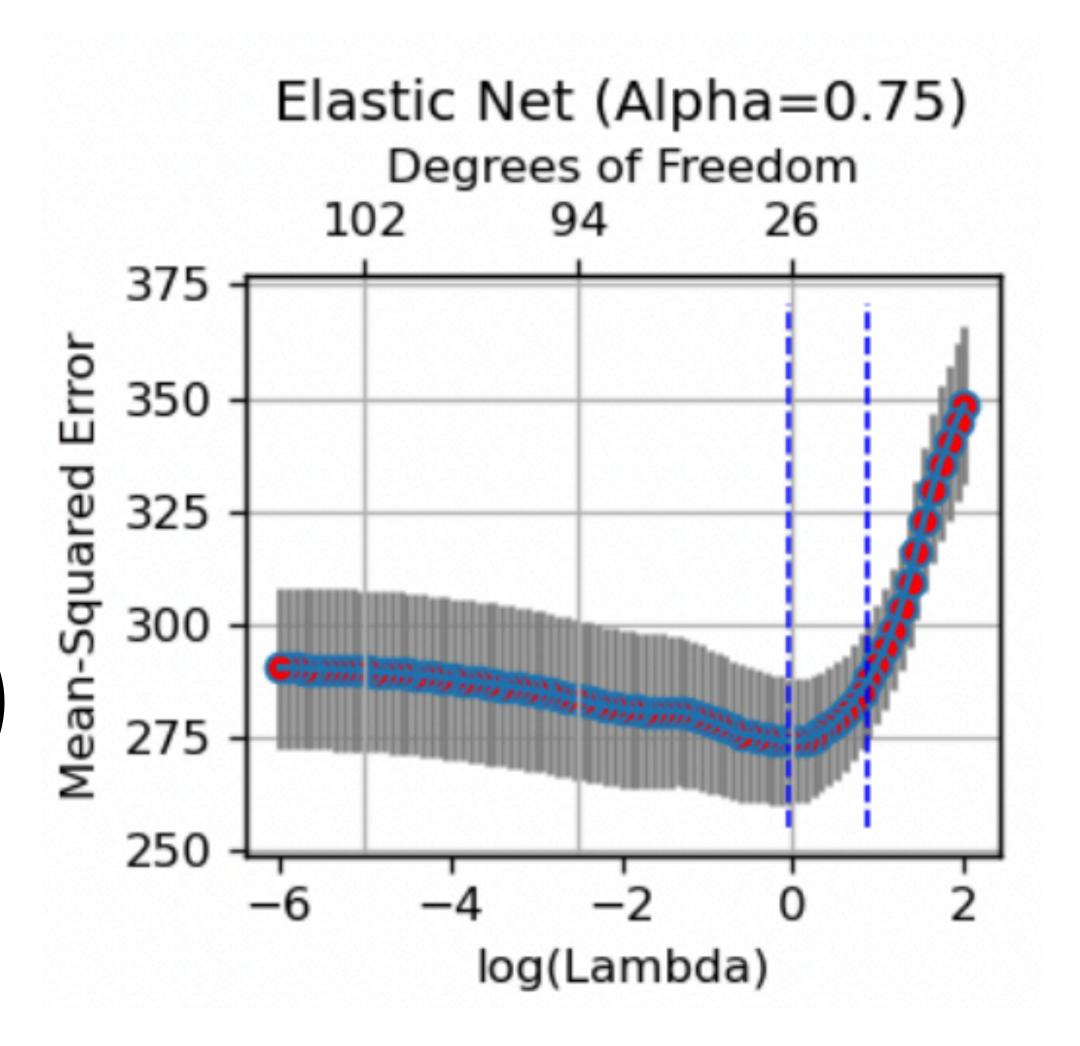
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Elastic Net

- Correlated explanatory variables
 - Lasso regularization may include only one
 - May result in worse predictions
- Elastic Net
 - ullet weighted on L_1 and L_2 norms
 - minimization goal:

$$\frac{1}{N}(\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^{T}(\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) + \lambda \left(\frac{1 - \alpha}{2} \|\boldsymbol{\beta}\|_{2}^{2} + \alpha \|\boldsymbol{\beta}\|_{1}\right)$$

- $0 \le \alpha \le 1$
 - $\alpha = 1$: Lasso. $\alpha = 0$: Ridge



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