

Project: Cross-validation for model selection

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Background

Setup and preliminary definitions

Let $\mathcal{D}_n := \{(y_i, \mathbf{x}_i) : i \in [n]\}$ be a set of independent data points drawn from a distribution $\mathbb{P}_{y, \mathbf{x}}$ for $(y, \mathbf{x}) \in \mathbb{R}^{1+p}$. We treat the \mathbf{x}_i as predictors of the outcome y_i , and we assume a linear model

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$$

where $\mathbf{X} = [\mathbf{x}_1 \ \mathbf{x}_2 \ \cdots \ \mathbf{x}_n]^\top \in \mathbb{R}^{n \times p}$ is the design matrix, $\mathbf{y} = [y_1 \ y_2 \ \cdots \ y_n]^\top$, and \mathbf{e} is a mean-zero random vector with $\text{Cov}(\mathbf{e}) = \sigma^2 \mathbf{I}_n$.

In the context of competing models

Define

$$\mathcal{L}_n(\alpha, \mathcal{D}_n) = \frac{1}{n} \sum_{i=1}^n \left(\mathbf{x}_i^\top \boldsymbol{\beta} + e_i - \mathbf{x}_{i\alpha}^\top \hat{\boldsymbol{\beta}}_\alpha \right)^2$$

Lemma 1

$$\mathbb{E} \left[\mathcal{L}_n(\alpha, \mathcal{D}_n) \mid \mathbf{X} \right] = \sigma^2 + \frac{1}{n} d_\alpha \sigma^2 + \frac{1}{n} \|M_\alpha \mathbf{X} \boldsymbol{\beta}\|^2$$

Proof.

$$\mathbb{E} [\mathcal{L}_n((\cdot) \alpha, \mathcal{D}_n), \mathbf{y}, \mathbf{X}] =$$

□