

Deviance in the case of Gaussian MLR model.

$$Y_i = x_i^T \beta + \epsilon_i, \quad \epsilon_i \stackrel{iid}{\sim} N(0, \sigma^2), \quad i=1, \dots, n.$$

The pdf of Y_i is $f_i(y_i | x_i, \beta, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma^2} \cdot \exp\left(-\frac{1}{2\sigma^2}(y_i - x_i^T \beta)^2\right)$

$$\begin{aligned} \text{Lik}(\beta, \sigma^2) &= \prod_{i=1}^n f_i(y_i | x_i, \beta, \sigma^2) = \dots = \\ &= (2\pi)^{-n/2} \cdot (\sigma^2)^{-n/2} \cdot \exp\left(-\frac{1}{2\sigma^2} \|\underline{y} - X\hat{\beta}\|_2^2\right). \quad \underline{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}. \end{aligned}$$

$$\text{Loglik}(\beta, \sigma^2) = -\frac{n}{2} \ln 2\pi - \frac{n}{2} \ln \sigma^2 - \frac{1}{2\sigma^2} \|\underline{y} - X\beta\|_2^2$$

$$-2LL(\beta, \sigma^2) = +n \cdot \ln 2\pi + n \ln \sigma^2 + \frac{\|\underline{y} - X\beta\|_2^2}{\sigma^2}$$

$$\text{Joint MLE for } (\beta, \sigma^2) \text{ is } \hat{\beta} = (X^T X)^{-1} X^T \underline{y}; \quad \hat{\sigma}^2 = \frac{\|\underline{y} - X\hat{\beta}\|_2^2}{n}$$

$$\text{If } \sigma^2 \text{ is known, Deviance} = n \cdot \ln 2\pi + n \cdot \ln \sigma^2 + \frac{\|\underline{y} - X\hat{\beta}\|_2^2}{\sigma^2}$$

$$\|\underline{y} - X\hat{\beta}\|_2^2 \equiv \text{RSS} - \text{resid sum of squares.}$$

$$\text{If } \sigma^2 \text{ is unknown, Deviance} = n \cdot \ln 2\pi + n \cdot \ln (\text{RSS}/n) + \frac{\text{RSS}}{\text{RSS}/n} = n$$

$$\text{Deviance} \equiv -2 \cdot \text{Loglik}(\hat{\theta}), \quad \hat{\theta} \text{ is the MLE for } \theta.$$

$$\theta \equiv \text{param. vector. Here, } \theta = (\beta, \sigma^2).$$