

# Fisher Information in MLE

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Let i.i.d sample  $x_1, \dots, x_n \sim F_x$ . The p.d.f is  $f_x(x|\theta)$  where  $\theta$  is the parameter and we use  $\theta_0$  to denote the value of underlying parameter  $\theta$ . Then the log-likelihood

$$l = \log L = \sum_{i=1}^n \log f(x_i|\theta).$$

## 1 Score function

The **score function** is the first derivative (**the gradient**) of log-likelihood

$$S(\mathbf{x}|\theta) = \frac{\partial l}{\partial \theta} \quad (1)$$

The MLE  $\hat{\theta}$  makes  $S(\mathbf{x}|\theta)$  equals to zero:

$$S(\mathbf{x}|\hat{\theta}) = 0.$$

Also under some regularity conditions

$$E_{\theta_0}(S(\mathbf{x}|\theta_0)) = \int \frac{\partial l}{\partial \theta} \cdot f(\mathbf{x}|\theta_0) d\mathbf{x} = \int \sum_{i=1}^n \frac{\partial \log f(x_i|\theta_0)}{\partial \theta} \prod_{i=1}^n f(x_i|\theta_0) dx_1 \cdots dx_n$$

Note that

$$\begin{aligned} & \int \frac{\partial \log f(x_1|\theta_0)}{\partial \theta} \prod_{i=1}^n f(x_i|\theta_0) dx_1 \cdots dx_n \\ &= \int \frac{\partial f(x_1|\theta_0)}{\partial \theta} \cdot \frac{1}{f(x_1|\theta_0)} \prod_{i=1}^n f(x_i|\theta_0) dx_1 \cdots dx_n \\ &= \int \left( \int \frac{\partial f(x_1|\theta_0)}{\partial \theta} dx_1 \right) E_{\theta_0}(S(\mathbf{x}|\theta_0)) \prod_{i=2}^n f(x_i|\theta_0) dx_2 \cdots dx_n \\ &= \frac{\partial}{\partial \theta} \int f(x_1|\theta_0) dx_1 \cdot \int \prod_{i=2}^n f(x_i|\theta_0) dx_2 \cdots dx_n \\ &= 0. \end{aligned}$$

Therefore

$$\mathbb{E}_{\theta_0} (S(\mathbf{x}|\theta_0)) = 0.$$

## 2 Fisher information

Fisher information (matrix) is the second order moment of the score function

$$I(\theta) = \mathbb{E}_{\theta_0} \left( S(\mathbf{x}|\theta) S(\mathbf{x}|\theta)^\top \right). \quad (2)$$

Since  $\mathbb{E}_{\theta_0} (S(\mathbf{x}|\theta_0)) = 0$ , the fisher information is the covariance matrix of  $S(\mathbf{x}|\theta_0)$

$$I(\theta_0) = \text{Var}_{\theta_0} (S(\mathbf{x}|\theta_0)).$$

Also it can be shown that

$$I(\theta_0) = -\mathbb{E} \left( \frac{\partial^2 l}{\partial \theta^2} \bigg|_{\theta=\theta_0} \right),$$

and

$$I^*(\theta_0) = I(\theta_0) / n,$$

where  $I^*(\theta_0)$  is the fisher info for only one single sample. Additionally

$$\sqrt{n} \left( \hat{\theta} - \theta_0 \right) \xrightarrow{D} N(0, I^*(\theta_0)^{-1}).$$

## References