

Fisher Information

Define Score gradient of log-likelihood w.r.t. model parameter

$$S(\theta) = \frac{\partial}{\partial \theta} \log \mathcal{L}(x | \theta)$$

Function of model parameter θ .

(If $\theta \rightarrow \theta_0$ the score becomes gradient vector $\frac{\partial}{\partial \theta_0} \log \mathcal{L}(x | \theta_0)$)

$$E \left[S(\theta) \mid \text{@ true params } \theta^* \right] = \left[\int dx \quad S(\theta) \quad \mathcal{L}(x | \theta) \right]$$

This is (known) true value of $S(\theta)$.

$$S(\theta^*) = \frac{\partial}{\partial \theta} \left|_{\theta=\theta^*} \log \mathcal{L}(x | \theta) \right.$$

$$= \int dx \quad \frac{1}{\mathcal{L}(x | \theta)} \frac{\partial \mathcal{L}(x | \theta)}{\partial \theta} \mathcal{L}(x | \theta)$$

$$= \int dx \quad \frac{\partial \mathcal{L}(x | \theta)}{\partial \theta}$$

$$= \frac{\partial^2}{\partial \theta^2} \int dx \mathcal{L}(x|\theta)$$

$$= \frac{\partial^2}{\partial \theta^2} I$$

$$E_x [S(\theta) | \theta'] = 0$$

Define Fisher Information as variance of score. $(\theta | \theta')$

$$I \geq 0 \iff \text{as variance.}$$

$$I(\theta) = \text{Var}_x (S(\theta))$$

$$= E_x [S(\theta)^2 | \theta'] - E_x [S(\theta) | \theta']^2$$

$$= \int dx S(\theta)^2 \mathcal{L}(x|\theta) \leftarrow \underline{\text{Def!}}$$

$$[S] = [\theta]^{-1} \quad [T] = [\phi]^{-2}$$

$$I(\theta) = - \int d\mathbf{x} \frac{\partial^2}{\partial \theta^2} \log \mathcal{L}(\mathbf{x}|\theta) \mathcal{L}(\mathbf{x}|\theta) \quad \leftarrow \underline{\text{Dep}^2}$$

I is related to curvature in $\log \mathcal{L}$ (w.r.t. θ)

left as exercise.

if ϕ is an alternative param, related by $\theta(\phi)$

$$I(\phi) = I(\theta) \left(\frac{\partial \theta}{\partial \phi} \right)^2$$

FIM

$$I_m(\theta) = - \int d\mathbf{x} \left[\frac{\partial^2}{\partial \theta_i \partial \theta_j} \log \mathcal{L}(\mathbf{x}|\theta) \right] \mathcal{L}(\mathbf{x}|\theta) \quad \leftarrow \begin{matrix} \text{in} \\ \text{n dimension} \end{matrix}$$

$$\log P(\theta | x) = \log \pi(\theta) + \log L(x|\theta) - \log Z$$

expand const θ'

$$close to \theta' \quad \frac{\partial}{\partial \theta} \log \pi \approx 0$$

$$\begin{aligned} \log P(\theta | x) &= \text{const} + (\theta - \theta') \frac{\partial}{\partial \theta} \log L(x|\theta) \\ &\quad + \frac{1}{2} (\theta - \theta')^2 \frac{\partial^2}{\partial \theta^2} \log L(x|\theta) \\ &\quad + \dots \end{aligned}$$

↓ Expectation x

$$= \text{const} - \frac{1}{2} (\theta - \theta')^2 I(\theta)$$

$$\text{width} \sim \frac{1}{\sqrt{I(\theta)}}$$

$$n_1 = S \text{ stars} \quad \text{in} \quad A_1 = 1 \text{ deg}^2$$

$$\begin{aligned}
I_1(S) &= \int dx \left(\frac{d^2}{d\phi^2} \log \mathcal{L}(x|\phi) \right)^2 \mathcal{L}(x|\phi) \\
&= \sum_{n_1=0}^{\infty} \left(\frac{n_1}{S} - A_1 \right)^2 \frac{(A_1 S)^{n_1} e^{-A_1 S}}{n_1!} \\
&= \sum_{n_1=0}^{\infty} \left(\frac{A_1^2}{S^2} - 2 \frac{A_1}{S} + A_1^2 \right) \frac{\mathcal{L}(n_1 | \mathcal{S})}{S} \\
&= \frac{A_1}{S} \left(\left[\frac{A_1^2 + A_1^2}{S^2} \right] - \frac{2A_1}{S} A_1 S \quad A_1^2 \right)
\end{aligned}$$

let m be actual # stars in over A_2

let n_2 be # stars detected

$$m | s \sim \text{Poisson}(\lambda s)$$

$$n_2 | m \sim \text{Binomial}(m, p)$$

