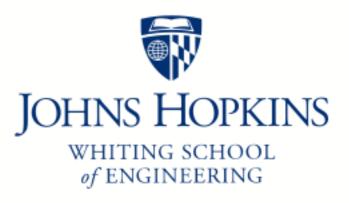
Johns Hopkins Engineering

625.464 Computational Statistics

Review of Maximum Likelihood Estimation, the Score Function, and Fisher Information Matrices

Module 2 Lecture 2D



$$X_1, \dots, X_n, iid$$
 $f(x|b)$

for $G = (O_1, \dots, C_p)$
 X_1, \dots, X_n
 $L(O) = \inf_{i=1}^n f(X_i|O)$
 $MaxImingor L(O)$

$$L(0)$$

$$L(0) = Log L(0)$$

$$L'(6) = 0$$

$$L'(6) = (\frac{100}{101}, \frac{100}{102}, ..., \frac{100}{10p}) = 0$$

$$Score function $E[L'(6)] = 0$$$

$$N(M, \sigma^{2})$$

$$S = (M, \sigma^{2})$$

$$f(X|D) = \frac{1}{2\pi\sigma^{2}} e^{-1/2} (\frac{X-M}{\sigma^{2}})^{2}$$

$$l(D|X) = -\frac{1}{2}ln(2\pi\sigma^{2}) - (\frac{X-M}{2\sigma^{2}})^{2}$$

$$\mathcal{L}(0|x) = -\frac{1}{2}\ln(2\pi\sigma^2) - \frac{(x-\mu)^2}{2\sigma^2}$$

$$\mathcal{L}(0) = \left(\frac{\partial Q}{\partial \mu}\right) \frac{\partial Q}{\partial \sigma^2}$$

$$= \left(\frac{x-\mu}{2\sigma^2}\right) - \frac{1}{2\sigma^2} + \frac{x-\mu}{2\sigma^2}$$

$$= \left(\frac{x-\mu}{2\sigma^2}\right) - \frac{x-\mu}{2\sigma^2} + \frac{x-\mu}{2\sigma^2} + \frac{x-\mu}{2\sigma^2}$$

$$= \left(\frac{x-\mu}{2\sigma^2}\right) - \frac{x-\mu}{2\sigma^2} + \frac{x-\mu}{2\sigma^2} + \frac{x-\mu}{2\sigma^2}$$

$$= \left(\frac{x-\mu}{2\sigma^2}\right) - \frac{x-\mu}{2\sigma^2} + \frac{x$$

Fisher Information Matrix

$$N(M_{1}G^{2})$$

Fisher Information Matrix

$$\int_{a}^{b} \left(\frac{x^{2}}{2} \right) - \int_{a}^{b} \left(\frac{x^{2}}{2} \right) - \int_{a$$

$$2''(0) = \frac{2^{2}10}{2^{2}10} = \frac{2^{2}10}{$$

$$-\frac{1}{5^{2}} - \frac{(x-h)}{5^{4}}$$

$$-\frac{(x-h)}{5^{4}}$$

$$-\frac{(x-h)^{2}}{5^{4}}$$

$$-\frac{(x-h)^{2}}{5^{6}}$$

Fisher Information Matrix