

Selected Subjects in Robotics and AI HW1

Daniel Haim Breger, 316136944

Technion

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1 Maximum Likelihood Estimation for Non-Gaussian Distribution

Let (X_1, X_2, \dots, X_n) be i.i.d samples from a Rayleigh distribution with unknown scale parameter $(\theta > 0)$:

$$f(x, \theta) = \frac{x}{\theta^2} e^{-x^2/(2\theta^2)}, \quad x \geq 0$$

1. Derive the maximum likelihood estimator $\hat{\theta}_{ML}$.
2. Show that it is a consistent estimator of θ .
3. Determine whether $\hat{\theta}_{ML}$ is biased. If it is, derive the bias expression.
4. Compute the Fisher Information and Cramer-Rao lower bound for estimating θ and check if $\hat{\theta}_{ML}$ attains it asymptotically.

1.1 Deriving MLE

The log-likelihood is

$$l(\theta) = \sum_{i=1}^n \left(\log X_i - 2 \log \theta - \frac{X_i^2}{2\theta^2} \right) \quad (1)$$

The definition of the MLE is

$$\hat{\theta}_{MLE} = \arg \max L(\theta, x) \quad (2)$$

To find the argmax we'll differentiate the log-likelihood:

$$\frac{dl}{d\theta} = \sum_{i=1}^n \left(-\frac{2}{\theta} + \frac{X_i^2}{\theta^3} \right) = \frac{-2n}{\theta} + \frac{1}{\theta^3} \sum_{i=1}^n X_i^2 \quad (3)$$

we require the derivative is equal to zero and find

$$\frac{dl}{d\theta} = \frac{-2n}{\theta} + \frac{1}{\theta^3} \sum_{i=1}^n X_i^2 = 0 \quad (4)$$

$$\rightarrow -2n\theta^2 + \sum_{i=1}^n X_i^2 = 0 \quad (5)$$

$$\rightarrow \theta_{\max} = \sqrt{\frac{1}{2n} \sum_{i=1}^n X_i^2} \quad (6)$$

verifying the point we found is indeed a maximum

$$\left. \frac{d^2l}{d\theta^2} \right|_{\theta_{\max}} = \frac{2n}{\theta^2} - \frac{3}{\theta^4} \sum_{i=1}^n X_i^2 \Big|_{\theta_{\max}} \quad (7)$$

$$= \frac{2n}{\theta_{\max}^2} - \frac{3}{\theta_{\max}^4} \cdot 2n\theta_{\max}^2 \quad (8)$$

$$= \frac{2n - 6n}{\theta_{\max}^4} = -\frac{4n}{\theta_{\max}^4} < 0 \quad (9)$$

Therefore it is indeed a maximum, so our MLE is

$$\hat{\theta}_{MLE} = \sqrt{\frac{1}{2n} \sum_{i=1}^n X_i^2} \quad (10)$$

1.2 Consistency Check

An estimator is called consistent if

$$\lim_{n \rightarrow \infty} \hat{\theta}_n = \theta \quad (11)$$

So we'll look at the limit

$$\lim_{n \rightarrow \infty} \hat{\theta}_{MLE} = \lim_{n \rightarrow \infty} \sqrt{\frac{1}{2n} \sum_{i=1}^n X_i^2} \quad (12)$$

Using the law of large numbers we can say

$$\lim_{n \rightarrow \infty} \sqrt{\frac{1}{2n} \sum_{i=1}^n X_i^2} = \sqrt{\frac{1}{2n} \sum_{i=1}^n \mathbb{E}(X_i^2)} = \sqrt{\frac{1}{2n} 2n\theta^2} = \theta \quad (13)$$

Using the 2nd moment of the Rayleigh distribution. Thus it is a consistent estimator.

1.3 Bias Check

The bias is defined as

$$\text{Bias}(\hat{\theta}) = \mathbb{E}(\hat{\theta}) - \theta \quad (14)$$

thus for our MLE estimator

$$\text{Bias}(\hat{\theta}) = \mathbb{E} \left(\sqrt{\frac{1}{2n} \sum_{i=1}^n X_i^2} \right) - \theta \quad (15)$$

$$= \frac{1}{\sqrt{2n}} \mathbb{E} \left(\sqrt{\sum_{i=1}^n X_i^2} \right) - \theta \quad (16)$$

to find the expectation value we'll notice that if $X_i \sim \text{Rayleigh}(\theta)$ then $\sum X_i \sim \Gamma(n, 2\theta^2)$. We can use the formula for the moments of the gamma distribution for the 1/2-th moment

$$\mathbb{E}(\sqrt{\sum X_i}) = \sqrt{2\theta} \frac{\Gamma(n + \frac{1}{2})}{\Gamma(n)} \quad (17)$$

and inserting back we find

$$\text{Bias}(\hat{\theta}) = \frac{1}{\sqrt{2n}} \mathbb{E} \left(\sqrt{\sum_{i=1}^n X_i^2} \right) - \theta \quad (18)$$

$$= \frac{1}{\sqrt{2n}} \sqrt{2\theta} \frac{\Gamma(n + \frac{1}{2})}{\Gamma(n)} - \theta \quad (19)$$

$$= \theta \left(\frac{1}{\sqrt{n}} \frac{\Gamma(n + \frac{1}{2})}{\Gamma(n)} - 1 \right) \quad (20)$$

The expression in the brackets is non-zero so the estimator is biased.

1.4 Fisher Information and CRLB

The Fisher Information is defined by

$$I = -\mathbb{E} \left(\frac{\partial^2}{\partial \theta^2} \log f \right) = -\mathbb{E} \left(\frac{\partial^2}{\partial \theta^2} \left(\log x - 2 \log \theta - \frac{x^2}{2\theta^2} \right) \right) \quad (21)$$

$$= -\mathbb{E} \left(\frac{\partial}{\partial \theta} \left(-\frac{2}{\theta} + \frac{x^2}{\theta^3} \right) \right) \quad (22)$$

$$= -\mathbb{E} \left(\frac{2}{\theta^2} - \frac{3x^2}{\theta^4} \right) \quad (23)$$

$$= - \left(\frac{2}{\theta^2} - \frac{3}{\theta^4} \mathbb{E}(x^2) \right) \quad (24)$$

$$= - \left(\frac{2}{\theta^2} - \frac{3}{\theta^4} 2\theta^2 \right) \quad (25)$$

$$= \frac{-2 + 6}{\theta^2} = \frac{4}{\theta^2} \quad (26)$$

And since the Fisher information is based on expectation value it is linear and thus the fisher information of n i.i.d variables is

$$I_n = \frac{4n}{\theta^2} \quad (27)$$

The CRLB is therefore

$$\text{Var}(\hat{\theta}_{MLE}) \geq \frac{\theta^2}{4n} \quad (28)$$

The MLE estimator is indeed asymptotically efficient as we saw in the lecture, but to show this we can use the asymptotic normality property

$$\sqrt{n} \left(\hat{\theta}_{MLE} - \theta \right) \rightarrow N\left(0, \frac{\theta^2}{4n}\right) \quad (29)$$

therefore asymptotically

$$\text{Var}(\hat{\theta}_{MLE}) = \frac{\theta^2}{4n} \quad (30)$$

which is indeed the CRLB.

2 Maximum A Posteriori Estimation with a Specific Prior

Assume the same Rayleigh distributed observations as in question 1, but now suppose the prior knowledge about θ is modeled as an inverse-gamma distribution

$$p(\theta) = \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{-(\alpha+1)} e^{-\beta/\theta}, \quad \theta > 0$$

1. Derive the MAP estimator $\hat{\theta}_{MAP}$
2. Compare $\hat{\theta}_{ML}$ and $\hat{\theta}_{MAP}$ in terms of bias and asymptotic behavior.
3. Analyze how the choice of prior parameters α and β influences the MAP estimate.
4. Discuss the limiting cases $(\alpha, \beta \rightarrow 0)$ and $(\alpha, \beta \rightarrow \infty)$ and interpret their effects on the posterior estimate.

3 Cramer-Rao Lower Bound and Efficiency

Let (X_1, X_2, \dots, X_n) be i.i.d samples from an exponential distribution

$$f(x, \lambda) = e^{-\lambda x}, \quad x \geq 0$$

where $\lambda > 0$ is unknown.

1. Derive the ML estimator $\hat{\lambda}_{ML}$.
2. Compute the Fisher Information.
3. Derive the CRLB for any unbiased estimator of λ .
4. Show that $\hat{\lambda}_{ML}$ achieves the CRLB and hence is an effective estimator.