COMS21202: Symbols, Patterns and Signals

Problem Sheet 3: Probabilistic Models

1. You were consulted by a Physics student who is trying to estimate the voltage (V) given current (I) and resistance (R) information. The student informs you that the physical model is

$$I = \frac{V}{R} + \epsilon$$

subject to a measurement error $\epsilon \sim \mathcal{N}(0, \sigma^2)$. Assuming *i.i.d* observations, the likelihood of p(D|V) where V is the model's only parameter and D is the observed data is equal to:

$$p(D|V) = \prod_{i} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2} \frac{(I_{i} - \frac{V}{R_{i}})^{2}}{\sigma^{2}}}$$

where I_i is the current value for observation i and R_i is the resistance value for observation i. Prove, using the Maximum Likelihood Estimation (MLE) recipe, that

$$V_{ML} = \sum \frac{I_i}{R_i} / \sum \frac{1}{R_i^2}$$

Answer:

Take the natural logarithm $\ln p(D|V) = N \ln \frac{1}{\sqrt{2\pi}\sigma} + \sum_{i} \frac{(I_i - \frac{V}{R_i})^2}{-2\sigma^2}$

Take the derivative $\frac{d}{dV} \ln p(D|V) = \frac{1}{\sigma^2} \sum_i \frac{1}{R_i} (I_i - \frac{V}{R_i})$

Equate the derivative to $0 - \frac{1}{\sigma^2} \sum_i \frac{1}{R_i} (I_i - \frac{V}{R_i}) = 0$

$$\begin{array}{l} \sum_{i}\frac{I_{i}}{R_{i}}-V_{ML}\sum_{i}\frac{1}{R_{i}^{2}}=0\\ V_{ML}=\sum\frac{I_{i}}{R_{i}}/\sum\frac{1}{R_{i}^{2}} \end{array}$$

2. For a given probabilistic model,

$$p(D|\theta) = b \ e^{-(3-\theta)^2}$$

where b is a normalising constant and a known prior of

$$p(\theta) = c e^{-\theta(\theta - 1)}$$

where c is a normalising constant, Find the maximum a posteriori value of the model parameters θ . Clearly show the steps you followed in finding the answer.

Answer:

$$p(D|\theta)p(\theta) = be^{-(3-\theta)^2}ce^{-\theta(\theta-1)}$$
(1)

$$\ln p(D|\theta)p(\theta) = \ln b + \ln c - (3-\theta)^2 - \theta(\theta - 1)$$
 (2)

$$p(D|\theta)p(\theta) = be^{-(3-\theta)^2}ce^{-\theta(\theta-1)}$$

$$\ln p(D|\theta)p(\theta) = \ln b + \ln c - (3-\theta)^2 - \theta(\theta-1)$$

$$\frac{d}{d\theta}\ln p(D|\theta)p(\theta) = 2(3-\theta) - 2\theta + 1$$
(3)

$$= -4\theta + 7 \tag{4}$$

$$-4\theta_{MAP} + 7 = 0 \tag{5}$$

$$\theta_{MAP} = \frac{7}{4} \tag{6}$$

3. Suppose that X is a discrete random variable with the following probability mass function, where $0 \le \theta \le 1$ is a parameter.

X	0	1	2	3
P(X)	$\frac{2\theta}{3}$	$\frac{\theta}{3}$	$\frac{2(1-\theta)}{3}$	$\frac{(1-\theta)}{3}$

The following 10 independent observations were taken from this distrubution:

- (a) What is the Maximum Likelihood estimate of θ
- (b) Assume you have prior knowledge that $p(\theta) = b \theta (1 \theta)$, what would the Maximum a Posteriori (MAP) be?

Answer:

(a) Following the MLE recipe,

$$p(D|\theta) = \prod_{i} P(d_{i}|\theta)$$

$$= \left(\frac{2\theta}{3}\right)^{2} \left(\frac{\theta}{3}\right)^{3} \left(\frac{2(1-\theta)}{3}\right)^{3} \left(\frac{1-\theta}{3}\right)^{2}$$

$$= c \theta^{5} (1-\theta)^{5} (where c is a constant)$$

Take the natural log, so

$$lnp(D|\theta) = \ln c + 5\ln\theta + 5\ln(1-\theta)$$

Take the derivative

$$\frac{d}{d\theta} \ln p(D|\theta) = \frac{5}{\theta} - \frac{5}{1-\theta}$$

Set the derivative to 0

$$\frac{5}{\theta_{ML}} - \frac{5}{1 - \theta_{ML}} = 0$$

$$5(1 - \theta_{ML}) - 5\theta_{ML} = 0$$

$$\theta_{ML} = \frac{1}{2}$$

(b) When introducing prior,

$$p(D|\theta)p(\theta) = \left(\frac{2\theta}{3}\right)^2 \left(\frac{\theta}{3}\right)^3 \left(\frac{2(1-\theta)}{3}\right)^3 \left(\frac{1-\theta}{3}\right)^2 b\theta(1-\theta)$$
$$= c\theta^6 (1-\theta)^6 (\text{where c is a constant})$$

Following the same formula as in (a), $\theta_{MAP} = 0.5$ (same as θ_{ML} for this particular case)