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Course: ECE276A

Assignment #: HW1

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Professor: Dr. Atanasov

#### Problem 4

$$X \sim \mathcal{N}(\mu, \overset{\text{known}}{\sigma^2})$$

↳ unknown

$\{x_i\}_{i=1}^n$ , where  $n$  is an independent samples obtained from  $X$ .

a) Formulate a maximum likelihood estimation (MLE) problem to determine the unknown mean of  $X$ .

$$\begin{aligned} \text{Apply Likelihood Function: } L(x_1, \dots, x_n | \mu, \sigma^2) &= \prod_{i=1}^n f_x(x_i | \mu, \sigma^2) ; f_x(x_i | \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}} \\ &= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}} \end{aligned}$$

$$L(x_1, \dots, x_n | \mu, \sigma^2) = (2\pi\sigma^2)^{-\frac{n}{2}} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2}$$

Take the natural logarithm of the likelihood function,

$$\begin{aligned} \lambda(x_1, \dots, x_n | \mu, \sigma^2) &= \ln(L(x_1, \dots, x_n | \mu, \sigma^2)) \\ &= \ln\left((2\pi\sigma^2)^{-\frac{n}{2}} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2}\right) \\ &= -\frac{n}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2 \\ &= -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln(\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2 \end{aligned}$$

$$\text{To } \max_{\mu, \sigma^2} \lambda(x_1, \dots, x_n | \mu, \sigma^2), \quad \frac{\partial}{\partial \sigma^2} \lambda(x_1, \dots, x_n | \mu, \sigma^2) = 0$$

$$\begin{aligned} \frac{\partial}{\partial \sigma^2} \left( -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln(\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2 \right) &= 0 \\ &= -\frac{n}{2\sigma^2} + \left( \frac{1}{2} \sum_{i=1}^n (x_i - \mu)^2 \right) \left( \frac{1}{\sigma^4} \right) \end{aligned}$$

$$\frac{\partial \lambda}{\partial \sigma^2} = \frac{1}{2\sigma^2} \left[ \frac{1}{\sigma^2} \left[ \sum_{i=1}^n (x_i - \mu)^2 \right] - n \right] = 0$$

$$\hat{\sigma}_{MLE}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2$$

$$\frac{\partial}{\partial \mu} \lambda(\mu, \sigma^2 | x_1, \dots, x_n) = 0 \Rightarrow \frac{\partial}{\partial \mu} \left( -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln(\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2 \right)$$

$$\frac{\partial \lambda}{\partial \mu} = \frac{1}{\sigma^2} \sum_{i=1}^n (x_i - \mu) = 0$$

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b.) Solve the problem in part (a) to obtain maximum likelihood estimate  $\hat{\mu}_{MLE}$

$$\frac{\partial l}{\partial \mu} = \frac{1}{\sigma^2} \sum_{i=1}^n (x_i - \mu) = 0$$

$$\left( \sum_{i=1}^n x_i - n\mu \right) = 0$$

$$\boxed{\hat{\mu}_{MLE} = \frac{1}{n} \sum_{i=1}^n x_i}$$

c.) Formulate a maximum a posteriori (MAP) problem to determine the unknown mean of  $X$ .

Suppose that a prior Gaussian distribution  $\mathcal{N}(\mu_0, \sigma_0^2)$  with known  $\mu_0$  and  $\sigma_0^2$  is available.

Given that  $f(\mu) = \frac{1}{\sqrt{2\pi\sigma_0^2}} e^{-\frac{(\mu-\mu_0)^2}{2\sigma_0^2}}$  → prior probability function.  
 apply Bayes' Rule:

$$f(\mu | x_1, \dots, x_n) = \frac{f(x_1, \dots, x_n | \mu) f(\mu)}{h(x_1, \dots, x_n)} \quad ; \quad H = h(x_1, \dots, x_n)$$

$$= \frac{\left[ (2\pi\sigma^2)^{-\frac{n}{2}} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2} \right] (2\pi\sigma_0^2)^{-\frac{1}{2}} e^{-\frac{(\mu-\mu_0)^2}{2\sigma_0^2}}}{H}$$

$$\text{To } \max_{\mu} \ln(f(\mu | x_1, \dots, x_n)) = \left( \sum_{i=1}^n -\ln(\sqrt{2\pi\sigma^2}) - \frac{(x_i - \mu)^2}{2\sigma^2} \right) - \ln(\sqrt{2\pi\sigma_0^2}) - \frac{(\mu - \mu_0)^2}{2\sigma_0^2}$$

$$\boxed{\frac{\partial \ln(f(\mu | x_1, \dots, x_n))}{\partial \mu} = \left( \sum_{i=1}^n \frac{x_i - \mu}{\sigma^2} \right) - \frac{\mu - \mu_0}{\sigma_0^2} = 0}$$

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d.) Solve the problem in part (c) to obtain the MAP estimate  $\hat{\mu}_{\text{MAP}}$ .

$$\frac{\partial \ln(f(\mu | x_1, \dots, x_n))}{\partial \mu} = 0$$

$$\left( \sum_{i=1}^n \frac{x_i - \mu}{\sigma^2} \right) - \frac{\mu - \mu_0}{\sigma_0^2} = 0$$

$$\frac{\mu - \mu_0}{\sigma_0^2} = \sum_{i=1}^n \frac{x_i - \mu}{\sigma^2}$$

$$= \frac{1}{\sigma^2} \left[ \left( \sum_{i=1}^n x_i \right) - n\mu \right]$$

$$\frac{(\sigma^2 + n\sigma_0^2)\mu}{\cancel{\sigma^2\sigma_0^2}} = \frac{(\sigma_0^2 \sum_{i=1}^n x_i) + \sigma^2 \mu}{\cancel{\sigma^2\sigma_0^2}}$$

$$\boxed{\hat{\mu}_{\text{MAP}} = \frac{(\sigma_0^2 \sum_{i=1}^n x_i) + \sigma^2 \mu}{\sigma^2 + n\sigma_0^2}}$$