

Assignment 2.4

Derive the *Maximum-Likelihood* estimates for the *Univariate Gaussian Distribution*! The *Probability Density Function* is defined as followed:

$$P(x|\theta) = \mathcal{N}(x|\mu, \sigma) := \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\}$$

Use the *independent and identical distribution* (i.i.d.) assumption about the sample set X :

$$\begin{aligned}\mathcal{L}(X := \{x_1, \dots, x_N\}) &= P(X|\theta) \\ &= \prod_{x_i \in X} P(x_i|\theta)\end{aligned}$$

$$L(\theta, X_1, \dots, X_N) \simeq P(X = x_1, \dots, x_N | \theta)$$

$$(i.i.d) = \prod_{i \in \{1, \dots, N\}} N(X_i = x_i | \mu, \sigma^2)$$

$$\begin{aligned}&= \prod_{i \in \{1, \dots, N\}} \frac{1}{(\sigma \cdot \sqrt{2\pi})} \cdot e^{-\frac{(x_i - \mu)^2}{2 \cdot \sigma^2}} \\ &= \left(\frac{1}{(\sigma \cdot \sqrt{2\pi})} \right)^N \cdot e^{\left(\sum_{i \in \{1, \dots, N\}} -\frac{(x_i - \mu)^2}{2 \cdot \sigma^2} \right)}\end{aligned}$$

Taking the logarithm of $P(X|\theta)$

$$= \ln \left(\left(\frac{1}{(\sigma \cdot \sqrt{2\pi})} \right)^N \right) + \sum_{i \in \{1, \dots, N\}} -\frac{(x_i - \mu)^2}{2 \cdot \sigma^2}$$

Differentiating wrt μ ,

$$\frac{\delta}{\delta\mu} \rightarrow \ln\left(\left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^N\right) - 0.5 \sum_{i \in \{1, \dots, N\}} \frac{(x_i - \mu)^2}{\sigma^2} = 0$$

$$0 - 0.5 \sum_{i \in \{1, \dots, N\}} \frac{1}{\sigma^2} \cdot 2 \cdot (x_i - \mu^*) \cdot (-1) = 0$$

$$\sum_{i \in \{1, \dots, N\}} \frac{1}{\sigma^2} \cdot (x_i - \mu^*) = 0$$

$$\sum_{i \in \{1, \dots, N\}} \frac{x_i}{\sigma^2} - \sum_{j \in \{1, \dots, N\}} \frac{\mu^*}{\sigma^2} = 0$$

$$\sum_{i \in \{1, \dots, N\}} \frac{x_i}{\sigma^2} = \sum_{j \in \{1, \dots, N\}} \frac{\mu^*}{\sigma^2}$$

$$\sum_{i \in \{1, \dots, N\}} x_i = N \cdot \mu^*$$

$$\boxed{\frac{1}{N} \sum_{i \in \{1, \dots, N\}} x_i = \mu^* = \mu^{\text{MLE}}}$$

Differentiating wrt σ ,

$$\frac{\delta}{\delta\sigma} \rightarrow \ln\left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^N - \sum_{i \in \{1, \dots, N\}} \frac{(x_i - \mu)^2}{2 \cdot \sigma^2} = 0$$

$$\frac{\delta}{\delta\sigma} \rightarrow \ln(1)^N - \ln(\sqrt{2\pi\sigma^2})^N - \sum_{i \in \{1, \dots, N\}} \frac{(x_i - \mu)^2}{2 \cdot \sigma^2} = 0$$

$$\frac{\delta}{\delta\sigma} \rightarrow 0 - \ln(\sqrt{2\pi\sigma^2})^N - \frac{(x_i - \mu)^2}{2 \cdot \sigma^2} = 0$$

$$\frac{\delta}{\delta\sigma} \rightarrow -\ln(2\pi\sigma^2)^{\frac{N}{2}} - \sum_{i \in \{1, \dots, N\}} \frac{(x_i - \mu)^2}{2 \cdot \sigma^2} = 0$$

$$\frac{\delta}{\delta\sigma} \rightarrow -\frac{N}{2} \ln(2\pi\sigma^2) - \sum_{i \in \{1, \dots, N\}} \frac{(x_i - \mu)^2}{2 \cdot \sigma^2} = 0$$

$$-\frac{N}{2} \frac{\delta}{\delta\sigma} (\ln(2\pi\sigma^2)) - \sum_{i \in \{1, \dots, N\}} \frac{(x_i - \mu)^2}{2} \frac{\delta}{\delta\sigma} (\sigma^{-2}) = 0$$

$$-\frac{N}{2} \cdot \frac{1}{2\pi\sigma^2} \cdot 2\pi \cdot \frac{\delta}{\delta\sigma} (\sigma^2) - \sum_{i \in \{1, \dots, N\}} \frac{(x_i - \mu)^2}{2} (-2 \cdot \sigma^{-3}) = 0$$

$$-\frac{N}{2} \cdot \frac{1}{2\pi\sigma^2} \cdot (4\pi\sigma) - \sum_{i \in \{1, \dots, N\}} \frac{(x_i - \mu)^2}{2} \left(\frac{-2}{\sigma^3} \right) = 0$$

$$-\frac{N}{\sigma} + \frac{1}{\sigma^3} \cdot \sum_{i \in \{1, \dots, N\}} (x_i - \mu)^2 = 0$$

$$\frac{1}{\sigma^3} \sum_{i \in \{1, \dots, N\}} (x_i - \mu)^2 = \frac{N}{\sigma}$$

$$\sum_{i \in \{1, \dots, N\}} (x_i - \mu)^2 = N \cdot \sigma^2$$

$$\boxed{\sqrt{\frac{1}{N} \sum_{i \in \{1, \dots, N\}} (x_i - \mu)^2} = \sigma^{\text{MLE}}}$$