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Homework 6

Exercises for Unit 6: Parametric pdf estimation

Solution for exercise 1

We have the problem

$$\min J(\mu) = \sum_{n=1}^{N} (x_n - \mu)^2$$

subject to $(\mu - \mu_0)^2 \le \rho$.

We define the Lagrangian function

$$L(\mu) = \sum_{n=1}^{N} (x_n - \mu)^2 + \lambda((\mu - \mu_0)^2 - \rho).$$

The derivative with respect to μ is

$$\frac{\partial L(\mu)}{\partial \mu} = -2\sum_{n=1}^{N} (x_n - \mu) + 2\lambda\mu - 2\lambda\mu_0$$
$$= -2\sum_{n=1}^{N} x_n + 2N\mu + 2\lambda\mu - 2\lambda\mu_0.$$

We set the derivative equal to zero and we solve the equation for finding μ .

$$\frac{\partial L(\mu)}{\partial \mu} = 0 \iff \mu = \frac{\lambda \mu_0 + \sum_{n=1}^{N} x_n}{N + \lambda}$$

Solution for exercise 2

The data are modeled by a pdf of the form

$$p(\mathbf{x}) = \sum_{j=1}^{m} P_j p(\mathbf{x}|j), \quad \sum_{j=1}^{m} P_j = 1, \quad \int_{-\infty}^{+\infty} p(\mathbf{x}|j) = 1$$

The parameter updating part of the Expectation Maximixation (EM) algorithm is

$$\arg \max_{P_1, P_2, \dots, P_M} \sum_{i=1}^{N} \sum_{j=1}^{m} P(j | \mathbf{x_i}) \ln P_j$$

subject to
$$\sum_{j=1}^{m} P_j = 1$$
.

(a) We define the Lagrangian function

$$L(P_1, P_2, \dots, P_m) = \sum_{i=1}^{N} \sum_{j=1}^{m} P(j|\mathbf{x_i}) \ln P_j + \lambda (\sum_{j=1}^{m} P_j - 1).$$

(b) We set the derivative of the Lagrangian function with respect to P_j equal to zero and we solve for P_j .

$$\frac{\partial L(P_1, P_2, \dots, P_m)}{\partial P_j} = 0 \iff \sum_{i=1}^N P(j|\mathbf{x_i}) \frac{1}{P_j} + \lambda = 0$$

So,

$$P_{j} = -\frac{\sum_{i=1}^{N} P(j|\boldsymbol{x_{i}})}{\lambda} \tag{1}$$

(c) Also we have

$$\sum_{j=1}^{m} P_j = 1. (2)$$

From (1),(2)

$$\sum_{i=1}^{m} \frac{\sum_{i=1}^{N} P(j|\mathbf{x_i})}{\lambda} = -1$$

and

$$\lambda = -\sum_{i=1}^{m} \sum_{i=1}^{N} P(j|\mathbf{x_i}) = -N.$$
(3)

(d) Finally, from (1),(3)

$$P_j = \frac{\sum_{i=1}^N P(j|\mathbf{x_i})}{N}.$$