

HW7

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Q2.

$$C = \{1, 2\}$$

Labeled samples = L

Unlabeled samples = $U=1$

features = 1

$$p(x|y=c, \underline{\theta}) = N(x|\mu_c, \sigma_c^2), \quad c=1, 2.$$

Priors & variances are constant.

Task:- Estimate μ_1, μ_2 using EM.

a) iteration:- t^{th}

E step:- Compute best est. of H as $p(H|D, \underline{\theta}^{(t)})$

$$\begin{aligned} \rightarrow p(H|D, \underline{\theta}^{(t)}) &= \prod_{h=L+1}^{L+U} p(y_h | \underline{x}_U, \underline{y}_L, \underline{x}_L, \underline{\theta}^{(t)}) \\ &= \prod_{h=L+1}^{L+U} p(y_h | \underline{x}_h, \underline{\theta}^{(t)}) \end{aligned}$$

As, $U=1$

$$\begin{aligned} \Rightarrow p(H|D, \underline{\theta}^{(t)}) &= p(y_h | \underline{x}_h, \underline{\theta}^{(t)}) \\ &= p(y_h = c_h | \underline{x}_h, \underline{\theta}^{(t)}) \quad , c_h = 1, 2 \\ &= y_{hc_h}^{(t)} \end{aligned}$$

Now,

$$y_{n|c_n^{(t)}} = p(y_n = c_n | x_n, \underline{\theta}^{(t)})$$

$$= \frac{p(x_n | y_n = c_n, \underline{\theta}^{(t)}) p(y_n = c_n | \underline{\theta}^{(t)})}{\sum_{y_n=1}^2 p(y_n = c_n | \underline{\theta}^{(t)}) p(x_n | y_n, \underline{\theta}^{(t)})}$$

$$= \frac{\frac{1}{\sqrt{2\pi\sigma_{c_n}^2}} \exp\left(-\frac{1}{2} \frac{(x_n - \mu_{c_n}^{(t)})^2}{\sigma_{c_n}^2}\right) \pi_{c_n}}{\sum_{y_n=1}^2 p(y_n = c_n | \underline{\theta}^{(t)}) p(x_n | y_n, \underline{\theta}^{(t)})}$$

$$\left\{ \begin{aligned} & (\pi_{c_1}) \left(\frac{1}{\sqrt{2\pi\sigma_1^2}} \exp\left(-\frac{1}{2} \frac{(x_n - \mu_1^{(t)})^2}{\sigma_1^2}\right) \right) \\ & + \\ & (\pi_{c_2}) \left(\frac{1}{\sqrt{2\pi\sigma_2^2}} \exp\left(-\frac{1}{2} \frac{(x_n - \mu_2^{(t)})^2}{\sigma_2^2}\right) \right) \end{aligned} \right\}$$

$$\Rightarrow \alpha_n^{(t)} = \frac{\pi_{c_1}}{\sqrt{2\pi\sigma_1^2}} \exp\left(-\frac{1}{2} \frac{(x_n - \mu_1^{(t)})^2}{\sigma_1^2}\right) + \frac{\pi_{c_2}}{\sqrt{2\pi\sigma_2^2}} \exp\left(-\frac{1}{2} \frac{(x_n - \mu_2^{(t)})^2}{\sigma_2^2}\right)$$

where π_{c_1} = Frequency of Labeled samples with class 1 (Priors)

π_{c_2} = Frequency of labeled samples with class 2 (Priors).

$$\Rightarrow p(D, H | \underline{\theta}) = p(H | D, \underline{\theta}) p(D | \underline{\theta})$$

$$p(D | \underline{\theta}) = \prod_{i=1}^L p(\underline{x}_i, y_i | \underline{\theta}) \prod_{h=L+1}^{L+V} p(\underline{x}_h | \underline{\theta})$$

$$= \left\{ \prod_{i=1}^L p(\underline{x}_i | y_i, \underline{\theta}) p(y_i | \underline{\theta}) \right\} \left\{ \sum_{y=1}^2 p(\underline{x}_h | y, \underline{\theta}) \pi_{c_y} \right\}$$

$$\Rightarrow p(D, H | \underline{\theta}) = \sum_{h=c_h} p(D | \underline{\theta})$$

$$= \left\{ \frac{p(\underline{x}_h | y_h = c_h, \underline{\theta}) p(y_h = c_h | \underline{\theta})}{\sum_{y=1}^2 p(y_v | \underline{\theta}) p(\underline{x}_h | y_v, \underline{\theta})} \right\} \cdot \left\{ \sum_{y=1}^2 p(\underline{x}_h | y, \underline{\theta}) \pi_{c_y} \right\}$$

$$\left\{ \prod_{i=1}^L p(\underline{x}_i | y_i, \underline{\theta}) p(y_i | \underline{\theta}) \right\} p(y_i = c_i)$$

$$\Rightarrow p(D, H | \underline{\theta}) = p(\underline{x}_h | y_h = c_h, \underline{\theta}) \pi_{c_h} \prod_{i=1}^L p(\underline{x}_i | y_i = c_i, \underline{\theta}) \pi_{c_i}$$

$$\text{where, } \pi_{c_i} = p(y_i = c_i | \underline{\theta}) = p(y_i = c_i)$$

$$\pi_{c_h} = p(y_h = c_h | \underline{\theta}) = p(y_h = c_h)$$

$$\begin{aligned} \underline{C} \quad \ln p(D, H | \underline{\theta}) &= \ln \{ p(x_n | y_n = c_n, \underline{\theta}) \} + \ln \{ \pi_{c_n} \} \\ &+ \sum_{i=1}^L \ln \{ p(x_i | y_i = c_i, \underline{\theta}) \} + \sum_{i=1}^L \ln \{ \pi_{c_i} \} \end{aligned}$$

→ Now, dropping terms that are not dependent on $\underline{\theta}$,

$$\Rightarrow \ln \{ p(D, H | \underline{\theta}) \} = \ln \{ p(x_n | y_n = c_n, \underline{\theta}) \} + \sum_{i=1}^L \ln \{ p(x_i | y_i = c_i, \underline{\theta}) \}$$

M Equation:-

$$\begin{aligned} \Rightarrow \underline{\theta}^{(t+1)} &= \underset{\underline{\theta}}{\operatorname{argmax}} E_{H|D, \underline{\theta}^{(t)}} \{ \ln p(D, H | \underline{\theta}) \} \\ &= \underset{\underline{\theta}}{\operatorname{argmax}} \sum_{c_n=1}^2 y_{nc_n}^{(t)} \left\{ \ln \{ p(x_n | y_n = c_n, \underline{\theta}) \} + \sum_{i=1}^L \ln \{ p(x_i | y_i = c_i, \underline{\theta}) \} \right\} \end{aligned}$$

$$= \underset{\underline{\theta}}{\operatorname{argmax}} \left\{ \sum_{c_n=1}^2 y_{nc_n}^{(t)} \left[\ln \left(\frac{1}{\sqrt{2\pi} \sigma_{c_n}^2} \exp \left(-\frac{1}{2} \frac{(x_n - \mu_{c_n})^2}{\sigma_{c_n}^2} \right) \right) \right] + \right.$$

(P.T.O)

$$\left. \sum_{h=1}^2 y_{hc_n}^{(t)} \left[\sum_{i=1}^L \ln \left(\frac{1}{\sqrt{2\pi} \sigma_{ci}^2} \exp \left(-\frac{1}{2} \frac{(x_i - \mu_{ci})^2}{\sigma_{ci}^2} \right) \right) \right] \right\}$$

(Dropping terms not dependent on $\underline{\theta}$)

$$\Rightarrow \underline{\theta}^{(t+1)} = \underset{\underline{\theta}}{\operatorname{argmax}} \left\{ \sum_{h=1}^2 y_{hc_n}^{(t)} \left[-\frac{1}{2} \frac{(x_n - \mu_{cn})^2}{\sigma_{cn}^2} \right] + \right.$$

$$\left. \left[\sum_{i=1}^L \left(-\frac{1}{2} \frac{(x_i - \mu_{ci})^2}{\sigma_{ci}^2} \right) \right] (y_{n1}^{(t)} + y_{n2}^{(t)}) \right\}$$

$$\Rightarrow \underline{\theta}^{(t+1)} = \underset{\underline{\theta}}{\operatorname{argmax}} \left\{ \sum_{h=1}^2 y_{hc_n}^{(t)} \left[-\frac{(x_n - \mu_{cn})^2}{\sigma_{cn}^2} \right] + \right.$$

$$\left. \sum_{i=1}^L \left[-\frac{(x_i - \mu_{ci})^2}{\sigma_{ci}^2} \right] \right\}$$

d. $l_1 = \#$ Labeled Samples with $c_i = 1$
 $l_2 = \#$ Labeled Samples with $c_i = 2$.
 (from c)

$$\Rightarrow \underline{\theta}^{(t+1)} = \underset{\underline{\theta}}{\operatorname{argmax}} \left\{ \sum_{h=1}^L y_{h1}^{(t)} \left[-\frac{(x_h - \mu_{c_h})^2}{\sigma_{c_h}^2} \right] + \sum_{i=1}^L \left[-\frac{(x_i - \mu_{c_i})^2}{\sigma_{c_i}^2} \right] \right\}$$

$$\Rightarrow \underline{\theta}^{(t+1)} = \underset{\underline{\theta}}{\operatorname{argmax}} \left\{ y_{h1}^{(t)} \left[-\frac{(x_h - \mu_1)^2}{\sigma_1^2} \right] + y_{h2}^{(t)} \left[-\frac{(x_h - \mu_2)^2}{\sigma_2^2} \right] \right.$$

$$\left. + \sum_{i=1}^{l_1} \left[[c_i = 1] \right] \left\{ -\frac{(x_i - \mu_1)^2}{\sigma_1^2} \right\} \right.$$

$$\left. + \sum_{i=1}^{l_2} \left[[c_i = 2] \right] \left\{ -\frac{(x_i - \mu_2)^2}{\sigma_2^2} \right\} \right\}$$

Now,

$$\frac{\partial}{\partial \mu_1} = y_{h1}^{(t)} \left[\frac{-2(x_h - \mu_1)(-1)}{\sigma_1^2} \right] + 0 + \sum_{i=1}^{l_1} \left[[c_i = 1] \right] \left\{ \frac{+2(x_i - \mu_1)}{\sigma_1^2} \right\} + 0.$$

$$\Rightarrow 0 = y_{h1}^{(t)} \frac{(x_h - \mu_1)}{\sigma_1^2} + \frac{1}{\sigma_1^2} \left\{ \sum_{i=1}^{l_1} [c_i = 1] x_i - l_1 \mu_1 \right\}$$

$$\Rightarrow 0 = \frac{y_{h1}^{(t)}(x_h) + \sum_{i=1}^{l_1} [c_i = 1] x_i}{\sigma_1^2} - \mu_1 \left\{ \frac{y_{h1}^{(t)} + l_1}{\sigma_1^2} \right\}$$

$$\Rightarrow \mu_1^{(t+1)} = \frac{y_{h1}^{(t)}(x_h) + \sum_{i=1}^{l_1} \mathbb{I}[c_i=1] x_i}{\{y_{h1}^{(t)} + l_1\}}$$

Similarly,

$\frac{\partial}{\partial v_2} = 0$, we get

$$\mu_2^{(t+1)} = \frac{y_{h2}^{(t)}(x_h) + \sum_{i=1}^{l_2} \mathbb{I}[c_i=2] x_i}{\{y_{h2}^{(t)} + l_2\}}$$

$$\therefore \underline{\theta}^{(t+1)} = \left[\frac{y_{h1}^{(t)}(x_h) + \sum_{i=1}^{l_1} \mathbb{I}[c_i=1] x_i}{\{y_{h1}^{(t)} + l_1\}}, \frac{y_{h2}^{(t)}(x_h) + \sum_{i=1}^{l_2} \mathbb{I}[c_i=2] x_i}{\{y_{h2}^{(t)} + l_2\}} \right]$$

e = i) $y_{h1}(t) = 0.3486$ (Also computed on computer)
(code file)

$y_{h2}(t) = 0.6513$

$$y_{h1}(t) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} \frac{(3-1.5)^2}{1}\right) \cdot 0.5$$

$$\frac{0.5}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} \frac{(3-1.5)^2}{1}\right) + \frac{0.5}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} \frac{(3-4)^2}{1}\right)$$

$$= \frac{0.0647588}{0.064788 + 0.120985}$$

$$= 0.3486$$

$y_{h2}(t) = 0.651359$

ii) $\mu_1(t+1) = \frac{(0.3486)(3) + (1+2)}{(0.3486) + 2}$
 $= 1.72264327$

$\mu_2(t+1) = \frac{(0.6513)(3) + (4)}{(0.6513) + 1}$
 $= 3.60558$