

Q1

$$a) \quad p(c|d) = \frac{p(c) p(d|c)}{p(d)} = \frac{\overset{\text{prior prob. of } c}{p(c)} \overset{\text{likelihood of } d}{p(d|c)}}{\sum_c \underset{\text{normalising constant}}{p(d, c)}}$$

$$b) \quad p(d=6 | c=t) = 1/6 \quad p(h) = p(c=t) = 1/2$$

$$p(d=6 | c=h) = 5/36 \quad [(1,5), (5,1), (3,3), (4,2), (2,4)]$$

$$\therefore p(\cancel{c=h} | d=6) = \frac{p(\cancel{c=h}) p(d=6 | c=h)}{p(\cancel{c=h}) p(d=6 | c=h) + p(\cancel{c=t}) p(d=6 | c=t)}$$

$$= \frac{5/36}{5/36 + 1/6} = \frac{5}{11}$$

Q2

$$a) \quad \lambda_{ML} = \underset{\lambda}{\operatorname{argmax}} \quad p(\{t_n\}_{n=1}^N | \lambda) = \underset{\lambda}{\operatorname{argmax}} \log p(\{t_n\}_{n=1}^N)$$

where

$$p(\{t_n\}_{n=1}^N | \lambda) = \prod_{n=1}^N p(t_n | \lambda) = \frac{1}{\lambda^N} \exp\left(-\sum_n t_n / \lambda\right)$$

$$b) \quad \frac{d}{d\lambda} \left[-N \log \lambda - \frac{1}{\lambda} \sum_n t_n \right] \bigg|_{\lambda=\lambda_{ML}} = 0$$

$$-\frac{N}{\lambda_{ML}} + \frac{1}{\lambda_{ML}^2} \sum_{n=1}^N t_n = 0$$

$$\Rightarrow \lambda_{ML} = \frac{1}{N} \sum_{n=1}^N t_n$$

c) we use running averages

$$\text{let } \lambda_{ML}^{(N)} = \frac{1}{N} \sum_{n=1}^N t_n = \frac{1}{N} S_N = \frac{N-1}{N} \lambda_{ML}^{(N-1)} + \frac{1}{N} t_N$$

\Rightarrow only need to store in memory $N-1$ & either S_{N-1} or $\lambda_{ML}^{(N-1)}$

\uparrow
of data seen so far @ previous step
 \uparrow
previous sum
 \uparrow
or previous estimate of λ

Q3

$$a) \mu_{\text{MAP}} = \underset{\mu}{\text{argmax}} \quad p(\mu | y, \sigma_{\mu}^2) = \underset{\mu}{\text{argmax}} \log p(\mu, y | \sigma_{\mu}^2)$$

$$b) \left. \frac{d}{d\mu} \left[\log p(\mu | \sigma_{\mu}^2) + \log p(y | \mu) \right] \right|_{\mu_{\text{MAP}}} = 0$$

$$\left. \frac{d}{d\mu} \left[-\frac{1}{2\sigma_{\mu}^2} \mu^2 + -\frac{1}{2} (y - \mu)^2 \right] \right|_{\mu_{\text{MAP}}} = 0$$

$$-\frac{1}{\sigma_{\mu}^2} \mu_{\text{MAP}} - (\mu_{\text{MAP}} - y) = 0$$

$$\Rightarrow \mu_{\text{MAP}} = \frac{y}{1 + 1/\sigma_{\mu}^2}$$

$$c) \mu_{\text{MAP}} \rightarrow \mu_{\text{ML}} \quad \text{as} \quad \sigma_{\mu}^2 \rightarrow \infty$$

Q4

$$a) \quad p(y_1 | x, w) = \frac{1}{1 + e^{-wx + b}} \quad \begin{array}{l} b = 0 \text{ (centered)} \\ w = -10 \end{array}$$

$$b) \quad y_2 = y_1 (\varepsilon \sigma_1 + \mu_1 + c_1 x) + (1 - y_1) (\varepsilon \sigma_2 + \mu_2 + c_2 x)$$

$$\begin{array}{lll} \sigma_1 = \frac{1}{2} & \mu_1 = 2 & c_1 = 4 \\ \sigma_2 = \frac{1}{10} & \mu_2 = -2 & c_2 = -2 \end{array} \quad \left. \vphantom{\begin{array}{lll} \sigma_1 = \frac{1}{2} & \mu_1 = 2 & c_1 = 4 \\ \sigma_2 = \frac{1}{10} & \mu_2 = -2 & c_2 = -2 \end{array}} \right\} \begin{array}{l} \text{approximate values} \\ \text{we find here} \end{array}$$

|||

$$p(y_2 | y_1, x) = y_1 N(y_2; c_1 x + \mu_1, \sigma_1^2) + (1 - y_1) N(y_2; c_2 x + \mu_2, \sigma_2^2)$$

Q5

a) Assignment step

$$S_n = \arg \min_k \|x_n - \underline{m}_k\|$$

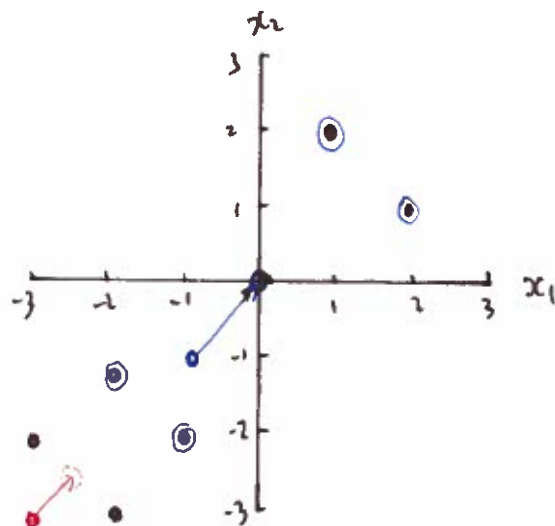
(assign each data point x_n to nearest cluster k^*)

Update step

$$\underline{m}_k = \text{mean}(\{x_n : S_n = k\})$$

(update cluster centres \underline{m}_k to be mean of data-points assigned to that cluster)

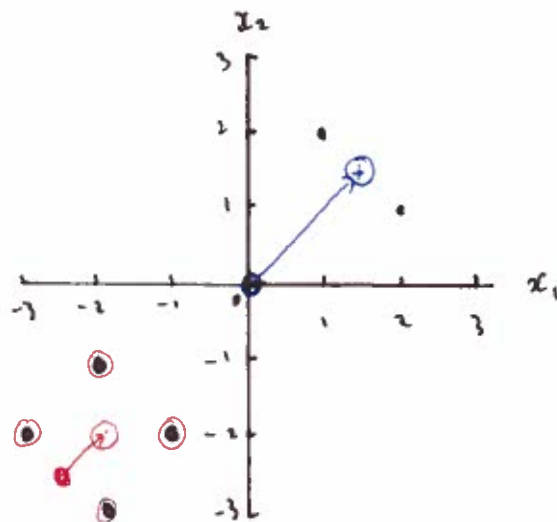
b)



initial $(-1, -1)$ $(-3, -3)$

update 1 $(0, 0)$ $(-2.5, -2.5)$

update 2 $(1.5, 1.5)$ $(-2, -2)$



Q6

a) $\alpha = 0.1$ as the KL divergence is minimized when $Q = P$

$$b) \quad KL(P \parallel Q) = P_1 \log \frac{P_1}{\alpha} + P_2 \log \frac{P_2}{1-2\alpha} + P_3 \log \frac{P_3}{\alpha}$$

$$\left. \frac{dKL}{d\alpha} \right|_{\alpha=\alpha^*} = \left(-\frac{P_1}{\alpha} + \frac{2P_2}{1-2\alpha} - \frac{P_3}{\alpha} \right) \Big|_{\alpha=\alpha^*} = 0$$

$$\Rightarrow (P_1 + P_3)(1-2\alpha^*) = 2P_2\alpha^*$$

$$\frac{P_1 + P_3}{2} = \alpha^*$$

$$\Rightarrow \alpha^* = \frac{0.6 + 0.2}{2} = 0.4$$

$$\left. \frac{d^2 KL}{d\alpha^2} \right|_{\alpha=\alpha^*} = \frac{0.6}{(\alpha^*)^2} + \frac{0.4}{(1-2\alpha^*)^2} + \frac{0.2}{(\alpha^*)^2} > 0 \Rightarrow \text{minimum}$$

Q7

$$a) p(x_1, x_2) = p(x_1) p(x_2 | x_1)$$

$$p(x_1=0, x_2=0) = 4/10 = 2/5$$

$$p(x_1=1, x_2=0) = 1/10$$

$$p(x_1=0, x_2=1) = 1/10$$

$$p(x_1=1, x_2=1) = 4/10 = 2/5$$

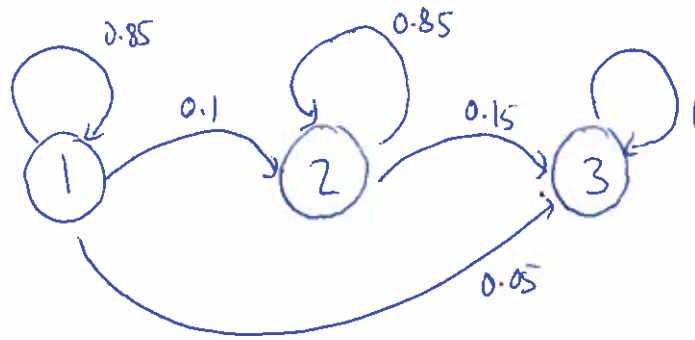
$$b) p(y_1, y_2) = \sum_{x_1, x_2} p(x_1, x_2) p(y_1 | x_1) p(y_2 | x_2)$$

$$= \frac{2}{5} \cdot N\left(\begin{bmatrix} y_1 \\ y_2 \end{bmatrix}; \begin{bmatrix} -1 \\ -1 \end{bmatrix}, \underline{\underline{I}}\right) + \frac{1}{10} \cdot N\left(\begin{bmatrix} y_1 \\ y_2 \end{bmatrix}; \begin{bmatrix} -1 \\ 1 \end{bmatrix}, \underline{\underline{I}}\right) \\ + \frac{1}{10} \cdot N\left(\begin{bmatrix} y_1 \\ y_2 \end{bmatrix}; \begin{bmatrix} 1 \\ -1 \end{bmatrix}, \underline{\underline{I}}\right) + \frac{2}{5} \cdot N\left(\begin{bmatrix} y_1 \\ y_2 \end{bmatrix}; \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \underline{\underline{I}}\right)$$

c) $p(y_{1:T})$ is a mixture of Gaussians with 2^T components each weighted by the probability of the latent sequence $p(x_{1:T})$ that produced them.

Q8

a)



b) every bike ends up in state 3

$$\begin{bmatrix} p(S_n=1) \\ p(S_n=2) \\ p(S_n=3) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

c)

$$\begin{bmatrix} 0.85 & 0 & a \\ 1 & 0.85 & b \\ 0.05 & 0.15 & 1-a-b \end{bmatrix} \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

\Rightarrow

$$\begin{aligned} a &= 0.15 \\ b &= 0.05 \\ c &= 0.8 \end{aligned}$$

ie. $\underline{T} \underline{P}_\infty = \underline{P}_\infty$