

1. (a) If a point is correctly classified :

$$\begin{aligned} Y^t g(x) &= \left(-\frac{1}{c-1}\right)^2 \cdot (c-1) + 1^2 \\ &= \frac{1}{c-1} + 1^2 \\ &= \frac{c}{c-1} \end{aligned}$$

If a point is incorrectly classified :

$$\begin{aligned} Y^t g(x) &= \left(-\frac{1}{c-1}\right)^2 \cdot (c-2) + \left(-\frac{1}{c-1}\right) \times 2 \\ &= \frac{c-2}{(c-1)^2} + \frac{-2}{c-1} \\ &= \frac{c-2+2-2c}{(c-1)^2} \\ &= \frac{-c}{(c-1)^2} \end{aligned}$$

(b). $\hat{u}_i = \exp\left[-\frac{1}{c}\left(\sum_{r=1}^{m-1} \beta_r Y_i^t g_r(x_i)\right)\right]$

$$\begin{aligned} \text{For } \beta \text{ fixed, } g_m &= \arg \min \sum_{i=1}^n \exp\left[-\frac{1}{c}\left(\sum_{r=1}^{m-1} \beta_r Y_i^t g_r(x_i) + \beta_m Y_i^t g_m(x_i)\right)\right] \\ &= \arg \min_{\beta} \sum_{i=1}^n \exp\left[-\frac{1}{c}\left(\sum_{r=1}^{m-1} \beta_r Y_i^t g_r(x_i)\right)\right] \cdot \exp\left[-\frac{1}{c} \beta_m Y_i^t g_m(x_i)\right] \\ &= \arg \min_{\beta} \sum_{i=1}^n \hat{u}_i \cdot \exp\left[-\frac{1}{c} \beta_m Y_i^t g_m(x_i)\right] \\ &= \arg \min_{\beta} \sum_{\substack{i | Y_i^t g_m(x_i) < 0 \\ i | Y_i^t g_m(x_i) > 0}} \hat{u}_i \exp\left[-\frac{1}{c} \beta \cdot \frac{c}{(c-1)^2}\right] + \sum_{\substack{i | Y_i^t g_m(x_i) > 0 \\ i | Y_i^t g_m(x_i) < 0}} \hat{u}_i \exp\left[-\frac{1}{c} \beta \cdot \frac{c}{c-1}\right] \\ &= \arg \min_{\beta} \sum_{i=1}^n \hat{u}_i \left(\mathbb{I}[Y_i^t g_m(x_i) < 0] \cdot A + \mathbb{I}[Y_i^t g_m(x_i) > 0] \cdot B \right) \\ &= \arg \min_{\beta} \sum_{i=1}^n \hat{u}_i \left(\mathbb{I}[Y_i^t g_m(x_i) < 0] \cdot A + (1 - \mathbb{I}[Y_i^t g_m(x_i) > 0]) \cdot B \right) \quad \text{since } \sum_{i=1}^n \hat{u}_i \text{ is fixed number, dividing the equation by } \sum_{i=1}^n \hat{u}_i \text{ doesn't change the minimization problem.} \\ &= \arg \min_{\beta} \sum_{i=1}^n \hat{u}_i [(A-B) \mathbb{I}[Y_i^t g_m(x_i) < 0] + B] \quad (\star) \end{aligned}$$

Since $A > B$, $A-B > 0$.

$\hat{u}_i > 0$, $B > 0$, $A-B$ and B are fixed.

So minimizing (\star) is to minimize $\sum_{i=1}^n \hat{u}_i \mathbb{I}[Y_i^t g_m(x_i) < 0] = em(g)$

Thus, $g_m = \arg \min_g em(g)$

Now g is fixed, $\sum_{i=1}^n \hat{u}_i \cdot \mathbb{I}[Y_i^t g(x_i) < 0] = em$

$$\begin{aligned} \beta_m &= \arg \min_{\beta} \sum_{i=1}^n \hat{u}_i [(A-B) \mathbb{I}[Y_i^t g(x_i) < 0] + B] \\ &= \arg \min_{\beta} \sum_{i=1}^n \hat{u}_i \cdot \mathbb{I}[Y_i^t g(x_i) < 0] \cdot (A-B) + \sum_{i=1}^n \hat{u}_i \cdot B \\ &= \arg \min_{\beta} em(A-B) + B \end{aligned}$$

$$\text{plug in } A = B^{\frac{1}{C-1}} \cdot L = \underset{\beta}{\operatorname{argmin}} \underset{\beta}{\operatorname{em}}(B^{\frac{1}{C-1}} - B) + B \\ = \underset{\beta}{\operatorname{argmin}} \underset{\beta}{\operatorname{em}}(1 - em)B + em \cdot B^{\frac{1}{C-1}} \quad (\star)$$

$$\frac{d(\star)}{dB} = 1 - em + em \cdot \left(-\frac{1}{C-1}\right) \cdot B^{-\frac{1}{C-1}-1}$$

$$\frac{d(\star)}{dB} = 0 \Leftrightarrow 1 - em = \frac{em}{C-1} B^{\frac{C}{C-1}}$$

$$\frac{(1 - em)(C-1)}{em} = B^{\frac{C}{C-1}}$$

$$B^{\frac{C}{C-1}} = \left(\frac{(1 - em)(C-1)}{em} \right)^{\frac{1-C}{C}}$$

So B_{\star} minimize (\star)

$$\begin{aligned} B_{\star} &= (1-C) \log B_{\star} \\ &= (1-C) \cdot \frac{1-C}{C} \cdot \left[\log \frac{1-em}{em} + \log(C-1) \right] \\ &= \frac{(C-1)^2}{C} \cdot \left[\log \frac{1-em}{em} + \log(C-1) \right] \end{aligned}$$

(9)

$$u = [u_1, u_2, \dots, u_n]$$

$$w = [w_1, w_2, \dots, w_n]$$

u and w are both initialized uniformly

So at 1st step, $u_i = w_i \forall i = 1, 2, \dots, n$

Now we show that if at k^{th} step, $u_i = w_i$, then at $(k+1)^{\text{th}}$ step, $u_i = w_i$

For any $i, j = 1, 2, \dots, n$

$$\frac{u_i^{(k)}}{u_j^{(k)}} = \frac{w_i^{(k)}}{w_j^{(k)}} \quad \text{since } u_i = w_i, u_j = w_j \text{ at } k\text{-th step.}$$

Now we discuss 4 cases:

① if $g(x_i)$ incorrect, $g(x_j)$ correct.

$$\frac{u_i^{(k+1)}}{u_j^{(k+1)}} = \frac{u_i^{(k)}}{u_j^{(k)}} \cdot (C-1) \cdot \frac{1-em}{em}$$

$$\frac{u_j^{(k+1)}}{u_i^{(k+1)}} = \frac{u_j^{(k)}}{u_i^{(k)}} \cdot \frac{\exp \left[-\frac{(C-1)^2}{C^2} \left(\log \frac{1-em}{em} + \log(C-1) \right) \cdot \frac{C}{(C-1)^2} \right]}{\exp \left[-\frac{(C-1)^2}{C^2} \left(\log \frac{1-em}{em} + \log(C-1) \right) \cdot \frac{C}{C-1} \right]}$$

$$= \frac{u_i^{(k)}}{u_j^{(k)}} \cdot \exp \left[\left(\frac{1}{C} + \frac{C-1}{C} \right) \cdot \left(\log \frac{1-em}{em} + \log(C-1) \right) \right]$$

$$= \frac{u_i^{(k)}}{u_j^{(k)}} \cdot \exp \left[\log \frac{1-em}{em} + \log(C-1) \right] = \frac{u_i^{(k)}}{u_j^{(k)}} \cdot (C-1) \cdot \frac{1-em}{em} = \frac{u_i^{(k)}}{u_j^{(k)}} \cdot (C-1) \cdot \frac{1-em}{em} = \frac{u_i^{(k)}}{u_j^{(k)}}$$

So $\frac{w_i^{(k+1)}}{w_j^{(k+1)}} = \frac{u_i^{(k+1)}}{u_j^{(k+1)}}$ for any i, j s.t. $g(x_i)$ is incorrect
 $g(x_j)$ is correct. (2)

② $g(x_i)$ is correct, $g(x_j)$ is incorrect

Similar to proof in case ① since we could simply have $\frac{w_j^{(k+1)}}{w_i^{(k+1)}} = \frac{u_j^{(k+1)}}{u_i^{(k+1)}}$ from (1)

③ $g(x_i)$ and $g(x_j)$ are both incorrect

$$\frac{w_i^{(k+1)}}{w_j^{(k+1)}} = \frac{w_i^{(k)}}{w_j^{(k)}} \cdot \frac{\frac{(C-1)}{C} \frac{1-\epsilon_m}{\epsilon_m}}{\frac{(C-1)}{C} \frac{1-\epsilon_m}{\epsilon_m}} = \frac{w_i^{(k)}}{w_j^{(k)}}$$

$$\begin{aligned} \frac{w_i^{(k+1)}}{w_j^{(k+1)}} &= \frac{u_i^{(k)}}{u_j^{(k)}} \cdot \frac{-\exp[-\frac{(C-1)^2}{C}(\log \frac{1-\epsilon_m}{\epsilon_m} + \log(C-1)) \cdot \frac{-C}{(C-1)^2}]}{-\exp[-\frac{(C-1)^2}{C}(\log \frac{1-\epsilon_m}{\epsilon_m} + \log(C-1)) \cdot \frac{-C}{(C-1)^2}]} \\ &= \frac{u_i^{(k)}}{u_j^{(k)}} \cdot 1 \end{aligned}$$

$$= \frac{w_i^{(k)}}{w_j^{(k)}} = \frac{w_i^{(k+1)}}{w_j^{(k+1)}}$$

So $\frac{w_i^{(k+1)}}{w_j^{(k+1)}} = \frac{u_i^{(k+1)}}{u_j^{(k+1)}}$ for any i, j s.t. $g(x_i)$ and $g(x_j)$ are both incorrect.

④ $g(x_i)$ and $g(x_j)$ are both correct

Similar to case ③, we can get $\frac{w_i^{(k+1)}}{w_j^{(k+1)}} = \frac{w_i^{(k)}}{w_j^{(k)}} = \frac{u_i^{(k)}}{u_j^{(k)}} = \frac{u_i^{(k+1)}}{u_j^{(k+1)}}$

So $\frac{w_i^{(k+1)}}{w_j^{(k+1)}} = \frac{u_i^{(k+1)}}{u_j^{(k+1)}}$ for any i, j s.t. $g(x_i)$ and $g(x_j)$ are both correct.

Denotation: $w_i^{(k+1)}, w_j^{(k+1)}$ are w_i and w_j at $(k+1)^{th}$ step

$w_i^{(k)}, w_j^{(k)}$ are w_i and w_j at k^{th} step

Similarly for $u_i^{(k+1)}, u_j^{(k+1)}, u_i^{(k)}, u_j^{(k)}$

From ①②③④, we've shown that $\frac{w_i^{(k+1)}}{w_j^{(k+1)}} = \frac{u_i^{(k+1)}}{u_j^{(k+1)}}$ for any $i, j = 1, 2, \dots, n$.

And since $\sum_{i=1}^n w_i^{(k+1)} = 1$, $\sum_{i=1}^n u_i^{(k+1)} = 1$,

we must have that $w_i^{(k+1)} = u_i^{(k+1)}$ for any $i = 1, 2, \dots, n$.

Thus, if $w_i = u_i$ at k^{th} step, $w_i = u_i$ at $(k+1)^{th}$ step.

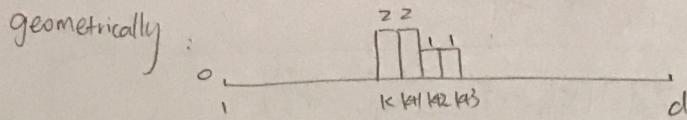
In conclusion, $w_i = u_i \quad \forall i = 1, 2, \dots, n$ at all the step.

3. (a). If $Y = k$

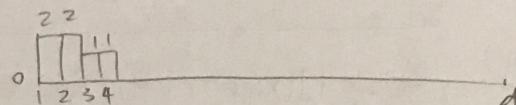
X will look like $[0, 0, \dots, 0, 2, 2, 1, 1, 0, \dots, 0]$

$$\begin{matrix} & \uparrow & \uparrow & \uparrow & \uparrow & \uparrow & \uparrow \\ & 1 & k_1 & k & k_{k1} & k_{k2} & k_{k3} & d \end{matrix}$$

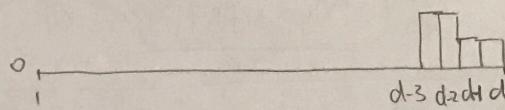
geometrically :



If $Y=1$: X will look like



If $Y=d-3$: X will look like



Geometrically, Y represents the start of signal of X .

(b). $\log P(X_1, \dots, X_d, Y)$

$$= \log (P(X_1, \dots, X_d | Y) \cdot P(Y))$$

$$= \log (P(X_1|Y) \cdot P(X_2|Y) \cdots P(X_d|Y) \cdot P(Y))$$

$$= \log (a_{XY} \cdot a_{X_{Y+1}} \cdot b_{X_{Y+2}} \cdot b_{X_{Y+3}} \cdot \prod_{\substack{j \leq Y \\ \text{or } j \geq Y+4}} C_{X_j} \cdot \pi_Y)$$

$$= \log a_{XY} + \log a_{X_{Y+1}} + \log b_{X_{Y+2}} + \log b_{X_{Y+3}} + \log \pi_Y + \sum_{\substack{j \leq Y \\ \text{or } j \geq Y+4}} \log C_{X_j}$$

(c). Fully Observed data $X_i, Y_i, i=1, 2, \dots, n$

$$\log P(X, Y | a, b, c, \pi_k)$$

$$= \log \prod_{i=1}^n P(X_i, Y_i | a, b, c, \pi_k)$$

$$= \log \prod_{i=1}^n P(Y_i, X_{i1}, \dots, X_{id}, Y_i | a, b, c, \pi_k)$$

$$= \sum_{i=1}^n \log P(X_{i1}, X_{i2}, \dots, X_{id}, Y_i | a, b, c, \pi_k)$$

$$= \sum_{i=1}^n \left(\sum_{j=1}^d \log P(X_{ij} | Y_i, a, b, c, \pi_k) + \log \pi_{Y_i} \right)$$

$$= \sum_{i=1}^n \left(\log a_{XY_i} + \log a_{X_{Y_i+1}} + \log b_{X_{Y_i+2}} + \log b_{X_{Y_i+3}} + \sum_{\substack{j \leq Y_i \\ \text{or } j \geq Y_i+4}} \log C_{X_{ij}} + \log \pi_{Y_i} \right)$$

$\hat{a}_r = \arg \max_{a_r} \log P(X, Y | a, b, c, \pi_k)$ for fixed b, c, π_k , subject to $a_0 + a_1 + a_2 = 1$

$\hat{b}_r = \arg \max_{b_r} \log P(X, Y | a, b, c, \pi_k)$ for fixed a_r, c, π_k , subject to $b_0 + b_1 + b_2 = 1$

$\hat{c}_r = \arg \max_{c_r} \log P(X, Y | a, b, c, \pi_k)$ for fixed a_r, b_r, π_k , subject to $c_0 + c_1 + c_2 = 1$

$\hat{\pi}_k = \arg \max_{\pi_k} \log P(X, Y | a, b, c, \pi_k)$ for fixed a_r, b_r, c_r , subject to $\sum_{k=1}^{d-3} \pi_k = 1$

$$\frac{d \log P(X, Y | a, b, c, \pi_k)}{da_r} = \sum_{i=1}^n \frac{1}{a_r} \cdot (I[X_{iY_i} = r] + I[X_{iY_{i+1}} = r]) \quad r = 0, 1, 2$$

$$\frac{d \log P(X, Y | a, b, c, \pi_k)}{da_r} = 0, \quad \sum_{r=0}^2 a_r (\frac{1}{a_r} - 1)$$

\Leftrightarrow solved as $\hat{a}_r = \frac{\sum_{i=1}^n (I[X_{iY_i} = r] + I[X_{iY_{i+1}} = r])}{2n}, \quad r = 0, 1, 2$

$$\frac{d \log P(X, Y | a, b, c, \pi_k)}{db_r} = \sum_{i=1}^n \frac{1}{b_r} \cdot (I[X_{iY_{i+2}} = r] + I[X_{iY_{i+3}} = r]) = 0, \quad \sum_{r=0}^2 b_r = 1$$

solved as $\hat{b}_r = \frac{\sum_{i=1}^n (I[X_{iY_{i+2}} = r] + I[X_{iY_{i+3}} = r])}{2n}, \quad r = 0, 1, 2$

$$\frac{d \log P(X, Y | a, b, c, \pi_k)}{dc_r} = \sum_{i=1}^n \frac{1}{c_r} \cdot \left(\sum_{\substack{j < Y_i \\ \text{or } j > Y_{i+4}}} I[X_{ij} = r] \right) = 0, \quad \sum_{r=0}^2 c_r = 1$$

solved as $\hat{c}_r = \frac{\sum_{i=1}^n (I[X_{ij} = r])}{(d-4)n}, \quad r = 0, 1, 2$

$$\frac{d \log P(X, Y | a, b, c, \pi_k)}{d \pi_k} = \sum_{i=1}^n \frac{1}{\pi_k} \cdot I[Y_i = k] \quad k = 1, 2, \dots, d-3$$

$$= 0 \quad \text{and} \quad \sum_{k=1}^{d-3} \pi_k = 1$$

solved as $\hat{\pi}_k = \frac{\sum_{i=1}^n I(Y_i = k)}{n}, \quad k = 1, 2, \dots, d-3$

(d). Y_i 's unobserved.

$$\begin{aligned} \text{① E step: } & \sum_{i=1}^n E_{Y_i | X_i, \theta^{old}} l(X_i, Y_i | \theta) \\ & = \sum_{i=1}^n \left[\sum_k P(Y_i | X_i, \theta^{old}) \cdot \log P(X_i, Y_i | \theta) \right] \quad (x) \end{aligned}$$

$$\begin{aligned} \text{For } P(Y_i | X_i, \theta^{old}) &= \frac{P(X_i, Y_i | \theta)}{P(X_i | \theta)} = \frac{P(X_i, Y_i | \theta)}{\sum_k P(X_i, Y_i | \theta)} \quad \text{let } v_{ik} = \log(P(Y_i = k, X_i | a, b, c, \pi)) \\ &= \frac{\exp(v_{ik})}{\sum_{k=1}^{d-3} \exp(v_{ik})} \quad \text{let } d = \log\left(\sum_{k=1}^{d-3} \exp(v_{ik})\right) \\ &= \frac{\exp(v_{ik})}{\exp(d)} \\ &= \exp(v_{ik} - d) \quad \text{let } \exp(v_{ik} - d) = w_{ik}, \quad \sum_{k=1}^{d-3} w_{ik} = 1 \end{aligned}$$

$$S_0(\theta) = \sum_{i=1}^n \left(\sum_{k=1}^{d-3} w_{ik} \cdot P(x_i, y_i=k | \theta) \right)$$

$$= \sum_{i=1}^n \sum_{k=1}^{d-3} w_{ik} (\log a_{x_{ik}} + \log a_{x_{ik+1}} + \log b_{x_{ik+2}} + \log b_{x_{ik+3}} + \log \pi_k + \sum_{\substack{j < k \\ \text{or } j > k+4}} \log c_{x_{ij}})$$

② M Step: $\hat{a}, \hat{b}, \hat{c}, \hat{\pi} = \underset{a, b, c, \pi}{\operatorname{argmax}} S(\theta)$

Similar to what we did in part (4),

$$\text{we get } \hat{a}_r = \frac{\sum_{i=1}^n \sum_{k=1}^{d-3} w_{ik} (I[X_{ik}=r] + I[X_{ik+1}=r])}{2n}$$

$$\hat{b}_r = \frac{\sum_{i=1}^n \sum_{k=1}^{d-3} w_{ik} (I[X_{ik+2}=r] + I[X_{ik+3}=r])}{2n}$$

$$\hat{c}_r = \frac{\sum_{i=1}^n \sum_{k=1}^{d-3} w_{ik} (\sum_{\substack{j < k \\ \text{or } j > k+4}} I[X_{ij}=r])}{(d-4) \cdot n} \quad r=0, 1, 2$$

$$\hat{\pi}_k = \frac{\sum_{i=1}^n w_{ik}}{n} \quad k=1, 2, \dots, d-3$$

Pseudo code:

- ① Initialize a, b, c, π
- ② Compute w_{ik} given $X, a^{old}, b^{old}, c^{old}, \pi^{old}$

③ update $a^{new} = \hat{a}_r$

$$b^{new} = \hat{b}_r$$

$$c^{new} = \hat{c}_r$$

$$\pi^{new} = \hat{\pi}_k$$

using w_{ik} in step ②

④ repeat ①③ until $\theta = \{a, b, c, \pi\}$,

$$\theta^{new} - \theta^{old} < \text{tolerance}$$