

Solutions EE641 Final
Fall 02

Problem 1

$$a) P\{X_i = k | Y = y\} = P\{X_i = k | Y_i = y_i\}$$

$$= \frac{p(y_i | k) \pi_k}{\sum_{l=0}^{M-1} p(y_i | l) \pi_l}$$

$$= \frac{e^{-\lambda_k} \lambda_k^{y_i} \pi_k}{\sum_l e^{-\lambda_l} \lambda_l^{y_i} \pi_l}$$

$$b) \log p(x, y | \theta) =$$

$$= \sum_{i=0}^{N-1} \{ \log p(y_i | x_i, \theta) + \log \pi_{x_i} \}$$

$$= \sum_{i=0}^{N-1} \{ y_i \log \lambda_{x_i} - \lambda_{x_i} - \log y_i! + \log \pi_{x_i} \}$$

$$= \left[\begin{aligned} & \sum_{i=0}^{N-1} y_i \log \lambda_{x_i} \\ & - \sum_{i=0}^{N-1} \lambda_{x_i} \\ & - \sum_{i=0}^{N-1} \log y_i! \\ & + \sum_{i=0}^{N-1} \log \pi_{x_i} \end{aligned} \right]$$

$$= \begin{aligned} & \sum_{k=0}^{M-1} a_k \log \lambda_k \\ & - \lambda_k \sum_{k=0}^{M-1} N_k \lambda_k \\ & + S(y) \\ & + \sum_{k=0}^{M-1} N_k \log \pi_k \end{aligned}$$

$$= \sum_{k=0}^{M-1} \{ a_k \log \lambda_k - N_k (\log \pi_k - \lambda_k) \} + S(y)$$

$\Rightarrow$ sufficient statistic for exponential distribution

$$\begin{aligned}
 c) \quad Q(\theta', \theta) &= \\
 &= E \left[\log p(y, x | \theta') \mid Y=y, \theta \right] \\
 &= E \left[\sum_{k=0}^{M-1} \left\{ a_k \log \lambda_k + N_k (\log \pi_k - \lambda_k) \right\} \mid Y=y, \theta \right] \\
 &\quad + S(y) \\
 &= \sum_{k=0}^{M-1} \left\{ \bar{a}_k (\log \lambda_k) + \bar{N}_k (\log \pi_k - \lambda_k) \right\} + S(y)
 \end{aligned}$$

$$d) \quad \theta'' = \arg \max_{\theta'} Q(\theta', \theta)$$

$$\pi_k'' = \frac{\bar{N}_k}{N}$$

$$\begin{aligned}
 \lambda_k'' &= \arg \max_{\lambda_k} \left\{ \bar{a}_k (\log \lambda_k) - \bar{N}_k \lambda_k \right\} \\
 &\quad + S(y) \\
 &= \frac{\bar{a}_k}{\bar{N}_k}
 \end{aligned}$$

2)

a)

$$\ell(y, x) = - \sum_{i \in S} -\log p(y_i | x) - \log p(x)$$

$$= \sum_{i \in S} \left\{ -y_i \log(H_{i*} x) + H_{i*} x + \log y_i! \right\}$$

$$+ \sum_{\{i, j\} \in C} b_{ij} |x_i - x_j|^2 + \sum_{i \in S} a_i |x_i|^2$$

b) Define

$$f_i(p) = -y_i \log p + p + \log y_i!$$

Then $f_i(p)$ is a convex function of p for $\mathbb{R} \rightarrow \mathbb{R}$ for $y_i \geq 0$.

So $f_i(H_{i*} x)$ is a convex function of x $\mathbb{R}^N \rightarrow \mathbb{R}$.

The sum of convex functions is convex, so $-\log p(y|x)$ is convex.

Notice that

$$-\log p(x) = \sum_{\{i, j\} \in C} b_{ij} |x_i - x_j|^2 + \sum_{i \in S} a_i |x_i|^2$$

is the sum of convex terms, so
it is convex.

But also notice that

$$\sum_{i \in S} a |x_i|^2 = a \|x\|^2 = a x^T I x$$

where I is a strictly positive definite

matrix $\Rightarrow$ strict convexity

Therefore $\ell(y, x)$ is strictly convex,

c) Yes it exists.

Select any $\tilde{x} \in \mathbb{R}^N$ such that
 $\forall i, \tilde{x}_i > 0$.

$$\text{Then } y_i = H_i * \tilde{x} > 0$$

$$\Rightarrow f_i(H_i * \tilde{x}) < \infty$$

$$\Rightarrow \sum_{i \in S} f_i(H_i * \tilde{x}) < \infty$$

$$\Rightarrow l(y, \tilde{x}) < \infty$$

Now consider the set

$$D = \{x \mid l(y, x) \leq l(y, \tilde{x})\}$$

the D is a bounded set

(need to prove this)

$\Rightarrow D$ is compact

$\Rightarrow$ There exists a minimum

d) Yes, it is unique

Strict convexity of $l(y, x)$ in x

(and $x \geq 0$)
(a convex
set)

$\Rightarrow$ (local minimum $\Rightarrow$ global minimum)

e) Yes, it is a continuous function of y .

Strict convexity of $\ell(y, x)$ in x
+

Continuity of $\ell(y, x)$ in (y, x)

3)

$$a) \quad \frac{d^2 Q(y, x)}{dy^2} > 3 \Rightarrow a(x) = \frac{3}{2}$$

$$\left. \frac{d Q(y, x)}{dy} \right|_{y=x} = \frac{d F(x)}{dx}$$

$$2 a(x) y + b(x) \Big|_{y=x} = \frac{d F(x)}{dx}$$

$$2 \cdot \frac{3}{2} x + b(x) = \frac{d F(x)}{dx}$$

$$b(x) = \frac{d F(x)}{dx} - 3x$$

$$Q(x, x) = f(x)$$

$$\frac{3}{2} x^2 + (f'(x) - 3x) x + c(x) = f(x)$$

$$c(x) = f(x) - \frac{3}{2} x^2 - (f'(x) - 3x) x$$

$$= f(x) + \frac{3}{2} x^2 - f'(x) x$$

b)

$$f(y) \leq Q(y, x)$$

$$f(x) = Q(x, x)$$

$$f(y) - f(x) \leq Q(y, x) - Q(x, x)$$

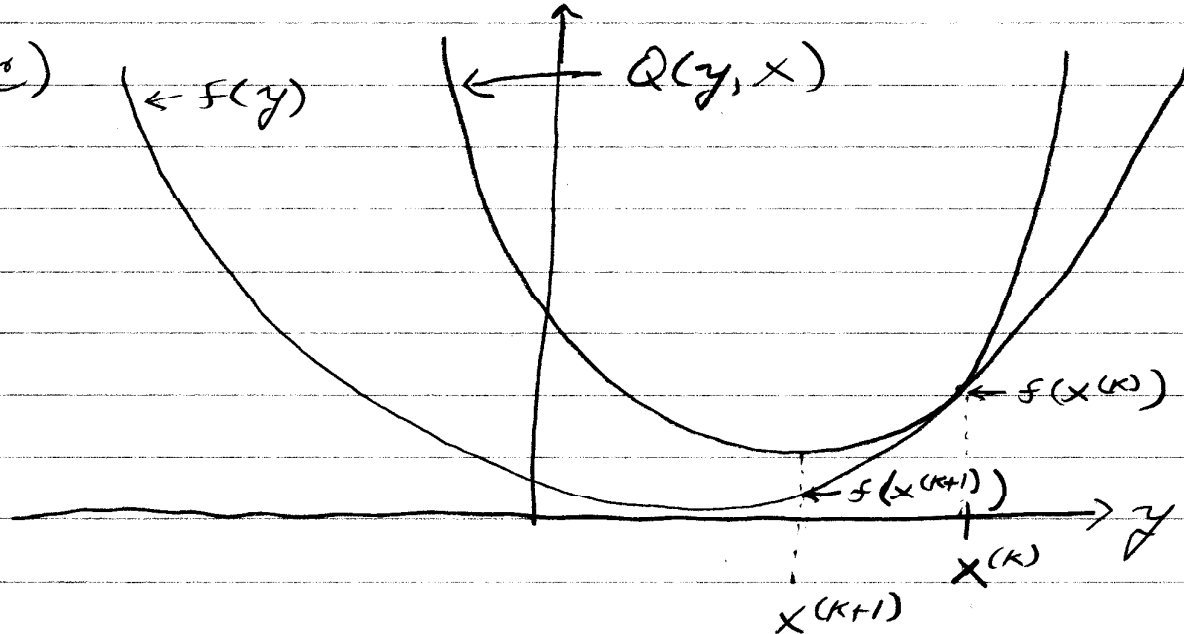
Since

$$Q(x^{(k+1)}, x^{(k)}) - Q(x^{(k)}, x^{(k)}) \leq 0$$

$$\Rightarrow f(x^{(k+1)}) - f(x^{(k)}) \leq 0$$

$$\Rightarrow f(x^{(k+1)}) < f(x^{(k)})$$

c)



4)

a)

$$\alpha_{n+1}(i) = \sum_{j=0}^{M-1} \alpha_n(j) P_{ji} f(Y_{n+1}|i)$$

b)

$$\beta_{n+1}(i) = \sum_{j=0}^{M-1} P_{ij} f(Y_{n+1}|j) \beta_n(j)$$

c)

$$\gamma_{n+1}(i) = \max_{j \in \{0, \dots, M-1\}} \{ P_{ij} f(Y_{n+1}|j) \gamma_n(j) \}$$