

# Homework 6

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**P[244] 1.**

The data given can be reconstructed by  $\mathbf{Y} = (y_1, \dots, y_n; i_1, \dots, i_m)$ , where  $i_k$  indicates the occurrence of a bulb kep lightning after time= $t$ . Since the measure on the sample space  $\mathcal{Y}$  is neither continuous nor discrete, we consider a random variable  $\mathbf{Z} = (z_1, \dots, z_n)$  where  $z_k$  represents the lifetime of a bulb if the experiment had continued after  $t$ . The joint distribution  $(\mathbf{Y}, \mathbf{Z})|\theta$  is

$$f(\mathbf{Y}, \mathbf{Z}|\theta; \forall k(i_k \sim z_k)) \propto \theta^{m+n} e^{-\theta(\sum_1^n y_j + \sum_1^m z_k)} \delta_{\forall k, i_k \sim z_k}$$

and the posterior is

$$\log \pi(\theta|\mathbf{Y}, \mathbf{Z}; \forall k(i_k \sim z_k)) = -\theta \left( \sum_1^n y_j + \sum_1^m z_k \right) + (m+n-1) \log \theta + C$$

and the target to be optimized is

$$\begin{aligned} & \mathbb{E}_{\mathbf{Z}|\mathbf{Y}, \theta; \forall k(i_k \sim z_k)} \left( -\theta \left( \sum_1^n y_j + \sum_1^m z_k \right) + (m+n-1) \log \theta \right) \\ &= -\theta \sum_1^n y_j + (m+n-1) \log \theta - \theta \sum_1^m \left[ \left( t + \frac{1}{\theta} \right) \cdot \delta_{i_k=1} + \left( \frac{1}{\theta} - \frac{t}{e^{t\theta} - 1} \right) \cdot \delta_{i_k=0} \right] \\ &= -\theta \left( \sum_1^n y_j + \sum_1^m \left( t \cdot \delta_{i_k=1} - \frac{t}{e^{t\theta} - 1} \cdot \delta_{i_k=0} \right) \right) + (m+n-1) \log \theta - m \end{aligned}$$

which means we should maximize (denoting  $M_1 := \#\{k|i_k = 1\}$  and  $M_0$  similarly)

$$-\theta \cdot \left( \sum_1^n y_j + t \cdot M_1 - \frac{t}{e^{t\theta} - 1} \cdot M_0 \right) + (m+n-1) \log \theta$$

which is hard to compute.

If we use E-M method: after getting  $\hat{\theta}_{(r)}$ ,

**Step (r+1):**

1. Expectation (up to  $+C$ )

$$E(\theta; \hat{\theta}_{(r)}) = -\theta \cdot \left( \sum_1^n y_j + t \cdot M_1 - \frac{t}{e^{t \cdot \hat{\theta}_{(r)}} - 1} \cdot M_0 + \frac{m}{\hat{\theta}_{(r)}} \right) + (m+n-1) \log \theta$$

2. Maximization

$$\theta_{(r+1)} = \frac{\sum_1^n y_j + t \cdot M_1 - \frac{t}{e^{t \cdot \theta_{(r)}} - 1} \cdot M_0 + \frac{m}{\theta_{(r)}}}{m + n - 1}$$

**P[244] 2.**

The joint distribution  $(\mathbf{Y}, \mathbf{Z})|\theta$  is

$$f(\mathbf{Y}, \mathbf{Z}|\theta; \forall k(i_k \sim z_k)) \propto \frac{1}{\theta^{m+n}} \delta_{(0, \theta)^{m+n}}$$

and the posterior is

$$\pi(\theta|\mathbf{Y}, \mathbf{Z}; \forall k(i_k \sim z_k)) \propto \theta^{-(m+n)} \delta_{\theta > \max\{y_j; z_k\}}$$

If we use E-M method: after getting  $\theta_{(r)}$ , assuming  $\theta_{(r)} > t$ ,  $\theta_{(r)} > \forall y_j$  and  $\theta > t$ ,

**Step (r+1)**

1. Expectation (up to  $\cdot C$ )

$$\begin{aligned} E(\theta; \theta_{(r)}) &= \mathbb{E}_{\mathbf{Z}|\mathbf{Y}, \theta_{(r)}; \forall k(i_k \sim z_k)} (\theta^{-(m+n)} \delta_{\theta > \max\{y_j; z_k\}}) \\ &= P_{\mathbf{Z}|\mathbf{Y}, \theta_{(r)}; \forall k(i_k \sim z_k)} (\theta > \max\{y_j; z_k\}) \cdot \theta^{-(m+n)} \\ &= \theta^{-(m+n)} (P_{\theta_{(r)}}(z_k < \theta | z_k \in (t, \theta_{(r)}))^{M_1} (P_{\theta_{(r)}}(z_k < \theta | z_k \in (0, t))^{M_0} \delta_{\theta > \max\{y_j\}}) \\ &= \theta^{-(m+n)} \left[ \min\left\{\frac{\theta - t}{\theta_{(r)} - t}, 1\right\} \right]^{M_1} \delta_{\theta > \max\{y_j\}} \end{aligned}$$

2. Maximization :

$$\theta_{(r+1)} = \max\{y_j, \min\{\frac{m+n}{m+n-M_1} \cdot t, \theta_{(r)}\}\}$$

So it's useless.

But if we try the usual method: the optimal solution is

$$\hat{\theta} = \max\{y_j, \frac{m+n}{m+n-M_1} \cdot t\}$$

So it is in a sense useless, especially when  $\theta_{(r)} < \frac{m+n}{m+n-M_1} \cdot t$ , it will never converge to the optimal point.