

4.5

$$\begin{aligned}
 (a) \quad \ell(\theta) &= \log p(x, z | \theta) \\
 &= \sum_i \log p(x_i | z_i, \theta) \cdot p(z_i | \theta) \\
 &= \sum_i \log \pi_j \cdot \left(\pi_j^{z_{ij}} \left(\frac{1}{x_{ij}!} e^{-\lambda_j} \lambda_j^{x_{ij}} \right)^{z_{ij}} \right) \\
 &= \sum_i \sum_j z_{ij} (\log \pi_j - \log x_{ij}! - \lambda_j + x_{ij} \log \lambda_j)
 \end{aligned}$$

$$\begin{aligned}
 \text{E-step: } \hat{z}_{ij} &= p(z_i = j | x, \hat{\theta}^{old}) \\
 &= \frac{p(x_i | z_i = j, \hat{\theta}^{old}) \cdot p(z_i = j | \hat{\theta}^{old})}{\sum_j p(x_i | z_i = j, \hat{\theta}^{old}) \cdot p(z_i = j | \hat{\theta}^{old})} \\
 &= \frac{\frac{1}{x_{ij}!} e^{-\hat{\lambda}_j} \hat{\lambda}_j^{x_{ij}} \cdot \pi_j}{\sum_k \pi_k \cdot \frac{1}{x_{ij}!} e^{-\hat{\lambda}_k} \hat{\lambda}_k^{x_{ij}}}
 \end{aligned}$$

$$\begin{aligned}
 \text{M-step} \quad \frac{\partial}{\partial \lambda_j} \ell(\theta) &= \sum_i \hat{z}_{ij} \left(-1 + \frac{x_{ij}}{\lambda_j} \right) = 0 \\
 \Rightarrow \quad \hat{\lambda}_j &= \frac{\sum_i \hat{z}_{ij} \cdot x_{ij}}{\sum_i \hat{z}_{ij}}
 \end{aligned}$$

Ps 2.1 M for a Poisson $\hat{\lambda} = \frac{\sum_i x_{ij}}{n}$

We denote $\hat{n}_j = \sum_i \hat{z}_{ij}$ is the number of points assigned to class j
 then $\sum_i \hat{z}_{ij} \cdot x_{ij}$ is the sum of x_{ij} value for those points

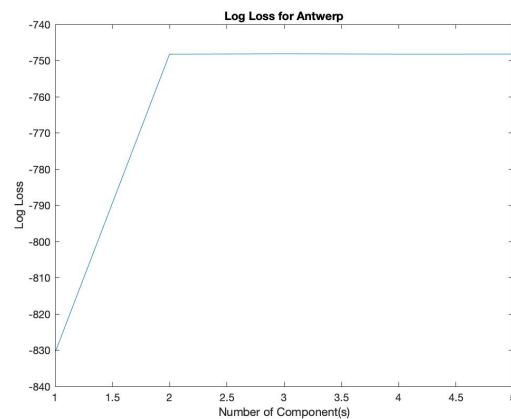
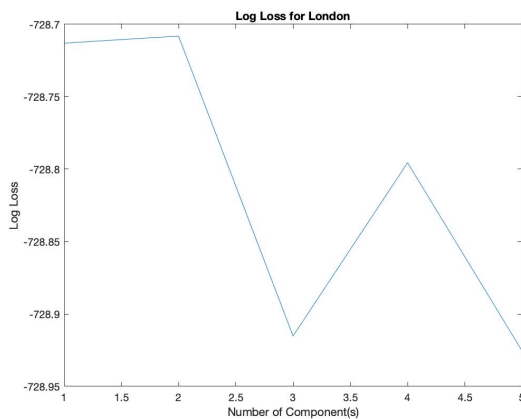
$$\hat{\lambda}_j = \frac{\sum_i \hat{z}_{ij} \cdot x_{ij}}{\hat{n}_j} \text{ is similar to an MLE for a Poisson with class } j$$

$$\begin{aligned}
 f &= \ell(\theta) + \lambda \left(\sum_j \pi_j - 1 \right) \\
 \frac{\partial}{\partial \pi_j} f &= 0 \Rightarrow \sum_i \hat{z}_{ij} \cdot \frac{1}{\pi_j} + \lambda = 0 \\
 \frac{\partial}{\partial \lambda} f &= 0 \Rightarrow \sum_j \pi_j = 1 \quad \sum_i \hat{z}_{ij} + \lambda \pi_j = 0 \\
 &\quad -\lambda \cdot \sum_j \pi_j = \sum_j \sum_i \hat{z}_{ij} = n \\
 \lambda &= -\frac{n}{\sum_j \pi_j} = -n
 \end{aligned}$$

$$\Rightarrow \hat{\pi}_j = \frac{\sum_i \hat{z}_{ij}}{n}$$

$\hat{\pi}_j$ denotes how many weights we assign to class j
according to the number of samples belonging to it

$$\begin{aligned} \text{C.b) } \log\text{-likelihood} &= \log p(x|\hat{\theta}) \\ &= \sum_i \log p(x_i|\hat{\theta}) \\ &= \sum_i \log \sum_j \hat{\pi}_j \text{Poisson}(x_i|\lambda_j) \end{aligned}$$



From these two figures plotted in MATLAB,
we see that log likelihood of London stays around -728
for $k=1$ to $k=5$, whereas Antwerp increases significantly
from $k=1$ to $k=2$, and then stay around -747.

lambda_Antwerp						lambda_london					
5x5 double						5x5 double					
	1	2	3	4	5		1	2	3	4	5
1	0.8958	0	0	0	0	1	0.9288	0	0	0	0
2	2.3059	0.2623	0	0	0	2	0.9953	0.8651	0	0	0
3	1.0881	0.1392	2.4459	0	0	3	1.1139	1.1220	0.6995	0	0
4	0.1202	0.5533	1.5377	2.6478	0	4	0.8226	0.7502	1.0724	1.1687	0
5	2.5882	1.6660	0.1522	0.1722	0.4533	5	1.1456	0.8189	1.1185	1.1084	0.6273

From the lambda, we see that London tends to have
a random attack, whereas in Antwerp, there are some
squares with higher probability of being attack.