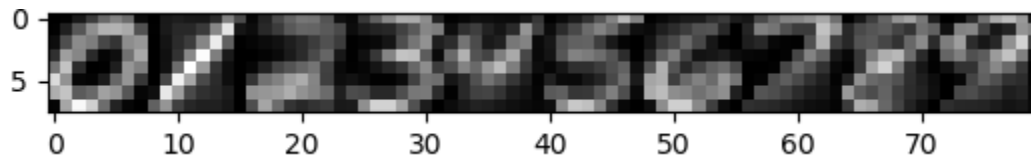


Q1.

a) Average Conditional Likelihood for training set is: -0.124624436669
Average Conditional Likelihood for test set is: -0.196673203255

b) Accuracy for training set is: 0.9814285714285714
Accuracy for test set is: 0.97275

c)



Q2.

a)

$$P(\theta) \propto \theta_1^{\alpha_1-1} \dots \theta_k^{\alpha_k-1}$$

$$P(x_i=j|\theta) = \theta_j$$

$$P(D|\theta) = \prod_{i=1}^n P(x_i=x_i|\theta) = \prod_{i=1}^n \theta_{x_i} = \prod_{j=1}^k \theta_j^{\sum_{i=1}^n 1(x_i=j)}$$

$$= \prod_{j=1}^k \theta_j^{\sum 1(x_i=j)}$$

$$\text{let } N_j = \sum 1(x_i=j) \quad = \prod_{j=1}^k \theta_j^{N_j}$$

$$P(\theta|D) \propto P(\theta) P(D|\theta)$$

$$= \prod_{k=1}^K \theta_k^{\alpha_k-1} \prod_{k=1}^K \theta_k^{N_k}$$

$$= \prod_{k=1}^K \theta_k^{\alpha_k-1+N_k}$$

$$P(\theta'|D) = \theta_{\text{pred}} = \int P(\theta|D) P(D'|D) d\theta$$

$$= \int \text{Dirch}(\alpha_1+N_1, \dots, \alpha_k+N_k) \theta_k d\theta$$

$$= E(\theta_k|D)$$

$$= \frac{N_k + \alpha_k}{N + \sum \alpha_k}$$

$$\begin{aligned}
 b) \quad \hat{\theta}_{MAP} &= \operatorname{argmax} P(\theta | D) \\
 &= \operatorname{argmax} P(D | \theta) P(\theta) \\
 &= \operatorname{argmax} \log P(\theta) + \log P(D | \theta)
 \end{aligned}$$

$$\begin{aligned}
 \# \log P(D | \theta) &= \log \prod_{k=1}^K \theta_k^{\alpha_k + N - 1} \\
 &= \sum_{k=1}^K (\alpha_k + N - 1) \log \theta_k
 \end{aligned}$$

$$\# \frac{\partial f}{\partial \theta_i} = \frac{\alpha_i + N_i - 1}{\theta_i} \quad \# \frac{\partial g}{\partial \theta_i} = 1$$

$$= \lambda \frac{\partial g}{\partial \theta_i}$$

$$\frac{\alpha_i + N_i - 1}{\theta_i} = \lambda$$

$$\sum (\alpha_i + N_i - 1) = \lambda \sum \theta_i$$

$$MAP = \frac{\alpha + N - 1}{N - K + \sum_{j=1}^K \alpha_j}$$

Q3.

a) E-step:

$$q(z=k) = P(z=k | x, \theta) = \frac{P(x|z, \theta) P(z | \theta)}{\sum_{j=0}^1 P(x|z_j, \theta) P(z_j | \theta)}$$

$$= \frac{[\pi_i P(x_i | z, \theta)] P(z | \theta)}{\sum_{j=0}^1 P(x | z_j, \theta) P(z_j | \theta)}$$

$$= \frac{[\pi_i P(x_i | \mu, \sigma)] (\pi^k (1-\pi)^{(1-k)})}{\sum_{j=0}^1 \pi_i P(x_i | \mu, \sigma) \pi^j (1-\pi)^{(1-j)}}$$

$$\mu(z) = E(z | x, \theta) = \frac{\pi \prod_{d=1}^D (\theta_d)^{x_d} (1-\theta_d)^{1-x_d}}{\sum_j \pi_j \prod_{d=1}^D (\theta_d^j)^{x_d} (1-\theta_d^j)^{1-x_d}}$$

b) set derivation to 0:

$$\frac{d}{d\mu} E[\log P(z, D, \mu)] = \sum_{i=1}^N E(z|x, \theta) \left[\frac{x}{\mu} + \frac{1-x}{1-\mu} \right] = 0$$

$$\sum_{i=1}^N E(z|x, \theta) [x(1-\mu) + (1-x)\mu] = \sum_{i=1}^N E(z|x, \theta) [-\mu + x] = 0$$

$$\mu = \frac{\sum_{i=1}^N q(z^{(i)}) x^{(i)}}{\sum_{i=1}^N q(z^{(i)})}$$

$$\mu = \frac{\sum_{i=1}^N m^{(i)} x^{(i)}}{N}$$