

HW7

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1) a) Let i be the datapoint index, k be the component, j be the dimension index of the D dimensional bit vector.

Then the log likelihood:

$$\begin{aligned} \ell(\mu) &= \sum_i \sum_k r_{ik} \log P(x_i | \theta_k) \\ &= \sum_i \sum_k r_{ik} \sum_j x_{ij} \log \mu_{kj} + (1 - x_{ij}) \log (1 - \mu_{kj}) \end{aligned}$$

$$\frac{\partial \ell}{\partial \mu_{kj}} = \sum_i r_{ik} \left(\frac{x_{ij}}{\mu_{kj}} - \frac{1 - x_{ij}}{1 - \mu_{kj}} \right) = \frac{1}{\mu_{kj} (1 - \mu_{kj})} \sum_i r_{ik} (x_{ij} - \mu_{kj}) = 0$$

thus the optimality condition is $\sum_i r_{ik} x_{ij} = \mu_{kj} \sum_i r_{ik}$

$$\begin{aligned} b) \ell(\mu) &= \sum_i \sum_k r_{ik} \log P(x_i | \mu_k) + \log P(\mu_k) \\ &= \sum_i \sum_k r_{ik} \left(\sum_j x_{ij} \log \mu_{kj} + (1 - x_{ij}) \log (1 - \mu_{kj}) \right) + (a-1) \log \mu_{kj} + (b-1) \log (1 - \mu_{kj}) \end{aligned}$$

$$\begin{aligned} \frac{\partial \ell}{\partial \mu} &= \sum_i \left(\frac{r_{ik} x_{ij} + a - 1}{\mu_{kj}} - \frac{r_{ik} (1 - x_{ij}) + b - 1}{1 - \mu_{kj}} \right) \\ &= \frac{1}{\mu_{kj} (1 - \mu_{kj})} \left[\sum_i r_{ik} x_{ij} - \left(\sum_i r_{ik} + a + b - 2 \right) \mu_{kj} + a - 1 \right] = 0 \end{aligned}$$

thus the optimality condition is $\sum_i r_{ik} x_{ij} + a - 1 = \left(\sum_i r_{ik} + a + b - 2 \right) \mu_{kj}$

2) let γ be the learning rate, then

$$\text{prox}_{\gamma}(x)_i = \begin{cases} x_i - \gamma & x_i > \gamma \\ 0 & |x_i| \leq \gamma \\ x_i + \gamma & x_i < -\gamma \end{cases}$$

$$\text{then } \frac{\partial \|x\|_1}{\partial x} = \frac{\partial \sum |x_i|}{\partial x_i} = \text{sign}(x_i) \Rightarrow \nabla \|x\|_1 = \text{sign}(x)$$

$$\begin{aligned} \text{then } \nabla \|Ax - b\|_2^2 + \lambda \|x\|_1 &= \nabla x^T A^T A x - 2b^T A x + b^T b + \lambda \|x\|_1 \\ &= 2A^T A x - 2b^T A + \lambda \text{sign}(x) \end{aligned}$$

