

# Homework #4

Simas Glinskis

December 1, 2016

Collaborated with Natasha Antropova

## Problem 1

We need to show that the two training objectives are equivalent. Let's call,

$$A = \sum_{i=1}^N (y_i - (w \cdot \phi(x_i) + w_0))^2 + \lambda \|w\|^2$$

$$B = \sum_{i=1}^N (y_i - (w \cdot \phi(x_i) + w_0))^2 + \alpha (\|w\|^2 - \tau)$$

Where we have used a Lagrange multiplier,  $\alpha$ , for the constraint.

For the optimal solutions, we know:

$$\nabla_w A(w_\lambda^*) = 0$$

and using the KKT conditions,

$$\nabla_w B(w_\alpha^*) = \nabla_w A(w_\alpha^*) = 0 \text{ and } \alpha (\|w_\alpha^*\|^2 - \tau) = 0$$

where  $w_\lambda^*$  are the optimal weights for a given  $\lambda$  and  $w_\alpha^*$  are the optimal weights for a given  $\alpha$ .

Say we set  $\tau = \|w_\lambda^*\|^2$ , then we have  $\lambda = \alpha$  and  $w_\lambda^* = w_\alpha^*$ , satisfying the KKT condition.

Therefore, the optimal weights will be the same for a  $\tau = \|w_\lambda^*\|^2$ .

## Problem 2

See attached notebook.

### Problem 3

The posterior probability  $\gamma_{i,c} = p(z_i = c|x_i; \theta, \pi)$  may be written as,

$$\gamma_{i,c} = \frac{\pi_c p(x_i|\theta_c)}{\sum_{l=1}^k \pi_l p(x_i|\theta_l)}$$

For a Bernoulli mixture,

$$p(x_i|\theta_c) = \prod_{j=1}^d \theta_{c,j}^{x_{i,j}} (1 - \theta_{c,j})^{(1-x_{i,j})}$$

Therefore,

$$\gamma_{i,c} = \frac{\pi_c \prod_{j=1}^d \theta_{c,j}^{x_{i,j}} (1 - \theta_{c,j})^{(1-x_{i,j})}}{\sum_{l=1}^k \pi_l \prod_{j=1}^d \theta_{l,j}^{x_{i,j}} (1 - \theta_{l,j})^{(1-x_{i,j})}}$$

### Problem 4

The M-step updates are,

$$\pi^{new}, \theta^{new} = \operatorname{argmax}_{\pi, \theta} \left[ \sum_{i=1}^N \sum_{c=1}^k \gamma_{i,c} (\log \pi_c + \log p(x_i; \theta_c)) \right]$$

Let us set,

$$A = \sum_{i=1}^N \sum_{c=1}^k \gamma_{i,c} (\log \pi_c + \log p(x_i; \theta_c)) = \sum_{i=1}^N \sum_{c=1}^k \gamma_{i,c} (\log \pi_c + \sum_{j=1}^d [x_{i,j} \log \theta_{c,j} + (1-x_{i,j}) \log (1-\theta_{c,j})])$$

Solving for  $\pi^{new}$  using Lagrange multipliers and differentiating,

$$A = \sum_{i=1}^N \sum_{c=1}^k \gamma_{i,c} (\log \pi_c) + \alpha (\sum_{c=1}^k \pi_c - 1) + \dots$$

$$\frac{\partial A}{\partial \pi_c} = 0 \rightarrow \sum_{i=1}^N \gamma_{i,c} = -\alpha \pi_c$$

$$\sum_{c=1}^k \sum_{i=1}^N \gamma_{i,c} = - \sum_{c=1}^k \alpha \pi_c \rightarrow \sum_{i=1}^N 1 = -\alpha \rightarrow \alpha = -N$$

$$\pi_k^{new} = \frac{1}{N} \sum_{i=1}^N \gamma_{i,k}$$

for a given subclass k.

Solving for  $\theta^{new}$ ,

$$\frac{\partial A}{\partial \theta_{k,r}} = 0 = \sum_{i=1}^N \gamma_{i,k} \left( \frac{x_{i,r}}{\theta_{k,r}} - \frac{1 - x_{i,r}}{1 - \theta_{k,r}} \right) = \sum_{i=1}^N \gamma_{i,k} (x_{i,r} - \theta_{k,r}) = 0$$

$$\theta_{k,r}^{new} = \frac{\sum_{i=1}^N \gamma_{i,k} x_{i,r}}{\sum_{i=1}^N \gamma_{i,k}}$$

for a given subclass k and parameter r.

## Problem 5

See attached notebook.