

Machine Learning Ex. 3

Aufg. 2) Free Energy is defined as:

$$F = \sum_n \sum_c \left[q^{(n)}(c) \log(p(\vec{x}^{(n)}, c | \theta)) - q^{(n)}(c) \log(q^{(n)}(c)) \right]$$

$$\text{It is } p(\vec{x} | c, \theta) = \frac{1}{\sqrt{\det(2\pi \Sigma_c)}} \exp\left(-\frac{1}{2} (\vec{x} - \vec{\mu}_c)^T \Sigma_c^{-1} (\vec{x} - \vec{\mu}_c)\right)$$

$$\text{and } p(c | \theta) = \pi_c \text{ fulfilling } \sum_c \pi_c = 1$$

With the product rule we know that $p(\vec{x}, c | \theta) = p(\vec{x} | c, \theta) p(c | \theta)$.

a) Maximize with respect to $\vec{\mu}$.

$$\frac{\partial F}{\partial \vec{\mu}_c} = 0 \Leftrightarrow 0 = \frac{\partial}{\partial \vec{\mu}_c} \left[\sum_n \sum_c q^{(n)}(c) \log \left(\frac{\pi_c}{\sqrt{\det(2\pi \Sigma_c)}} \exp\left(-\frac{1}{2} (\vec{x} - \vec{\mu}_c)^T \Sigma_c^{-1} (\vec{x} - \vec{\mu}_c)\right) - q^{(n)}(c) \log(q^{(n)}(c)) \right) \right]$$

Using $\frac{\partial}{\partial \vec{\mu}} q^{(n)}(c) = 0$ and since Σ_c is the diagonal matrix of the variances it is $\frac{\partial}{\partial \vec{\mu}} \Sigma_c = 0$ and $\frac{\partial}{\partial \vec{\mu}} \Sigma_c^{-1} = 0$ as a consequence we have not only $\frac{\partial}{\partial \vec{\mu}} \log(\det(\Sigma_c)) = \text{tr}\left(\Sigma_c^{-1} \frac{\partial \Sigma_c}{\partial \vec{\mu}}\right) = 0$

but can also use $\log(a \cdot b) = \log(a) + \log(b)$ together with the linearity of the derivative and get:

$$\begin{aligned} \frac{\partial F}{\partial \vec{\mu}_c} &= \sum_n \sum_c \left[-\frac{1}{2} \cdot \frac{1}{\sqrt{2\pi}} \frac{1}{\det(\Sigma_c)^{3/2}} \text{tr}\left(\Sigma_c^{-1} \frac{\partial \Sigma_c}{\partial \vec{\mu}}\right) + \left(-\frac{1}{2}\right) (-2) \Sigma_c^{-1} (\vec{x}^{(n)} - \vec{\mu}_c) + \left(-\frac{1}{2}\right) (\vec{x}^{(n)} - \vec{\mu}_c)^T \frac{\partial \Sigma_c^{-1}}{\partial \vec{\mu}} (\vec{x}^{(n)} - \vec{\mu}_c) \right] q^{(n)}(c) \\ &\quad \cdot \delta_{cc} = 0 \end{aligned}$$

$$\begin{aligned} \Rightarrow 0 &= + \sum_n q^{(n)}(c) (\vec{x}^{(n)} - \vec{\mu}_c) \Rightarrow \sum_n q^{(n)}(c) \vec{x}^{(n)} = \sum_n q^{(n)}(c) \vec{\mu}_c \\ &\Rightarrow \vec{\mu}_c = \frac{\sum_n q^{(n)}(c) \vec{x}^{(n)}}{\sum_n q^{(n)}(c)} \end{aligned}$$

b) Maximize π_c with the constraint $\sum_c \pi_c = 1$

$$\frac{\partial F}{\partial \pi_c} + \lambda \frac{\partial}{\partial \pi_c} \left(\sum_c \pi_c - 1 \right) = 0 \quad \forall c$$

$$\Rightarrow \frac{\partial}{\partial \pi_c} \left(\sum_n \sum_c q^{(n)} \log(\pi_c) \right) + \lambda \left(\sum_c \delta_{cc'} \right) = 0$$

$\underbrace{\hspace{10em}}_{=1}$

$$\Rightarrow \sum_n q^{(n)} \frac{1}{\pi_c} + \lambda = 0 \quad (*)$$

From this follows $\lambda \pi_c = - \sum_n q^{(n)} \quad \forall c$

and summing over c gets

$$\lambda \underbrace{\sum_c \pi_c}_{=1} = - \sum_n \underbrace{\sum_c q^{(n)}}_{=1} = - \sum_n 1 = -N$$

So with $\lambda = -N \quad (*)$ results in:

$$\pi_c = \frac{1}{N} \sum_n q^{(n)}$$