

Q2(d) The expectation of the log likelihood function with regularization looks like the following.

$$\alpha = \sum_{t=1}^N \sum_{i=1}^K y(z_i^t) \left( \log \pi_i + \log \frac{1}{(2\pi)^{d/2} |\Sigma_i|^{1/2}} e^{-1/2 (x^t - \mu_i)^T \Sigma_i^{-1} (x^t - \mu_i)} \right) - \frac{\lambda}{2} \sum_{i=1}^K \sum_{j=1}^d (\Sigma_i^{-1})_{jj}$$

On taking the partial derivative of  $\alpha$  wrt to  $\Sigma^{-1}$  and equating that to 0 we have

$$\frac{\partial \alpha}{\partial \Sigma^{-1}} = \sum_{t=1}^N \sum_{i=1}^K (z_i^t) \left( \frac{\Sigma_i}{2} - \frac{1}{2} (x^t - \mu_i) (x^t - \mu_i)^T \right) - \frac{\lambda I}{2}$$

$$\frac{\partial \alpha}{\partial \Sigma^{-1}} = 0$$

$$\Rightarrow \sum_{t=1}^N \sum_{i=1}^K (z_i^t) \left( \frac{\Sigma_i}{2} - \frac{1}{2} (x^t - \mu_i) (x^t - \mu_i)^T \right) - \frac{\lambda I}{2}$$

$$\frac{\Sigma}{2} N_i = \frac{1}{2} \sum_{i=1}^N y(z_i^t) \left( \frac{\Sigma_i}{2} - \frac{1}{2} (x^t - \mu_i) (x^t - \mu_i)^T \right) + \frac{\lambda I}{2}$$

$$\Sigma = \frac{1}{N} \sum_{t=1}^N y(z_i^t) (x^t - \mu_i) (x^t - \mu_i)^T + \frac{\lambda I}{N_i}$$

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Therefore we have

$$\Sigma = \frac{1}{N} \sum_{t=1}^N y(z_i^t) (x^t - \mu_i) (x^t - \mu_i)^T + \frac{\lambda I}{N_i}$$