

3.b

For each target vector, we have:

$$p(t_i|W, \Sigma) = N(t_i|y(x_i, W), \Sigma) = \frac{1}{\sqrt{(2\pi)^K \det \Sigma}} e^{-\frac{1}{2}(t_i - y(x_i, W))^T \Sigma^{-1} (t_i - y(x_i, W))}$$

So the log-likelihood is given by:

$$\begin{aligned} \log p(t_i|W, \Sigma) &= \log \frac{1}{\sqrt{(2\pi)^K \det \Sigma}} e^{-\frac{1}{2}(t_i - y(x_i, W))^T \Sigma^{-1} (t_i - y(x_i, W))} = \\ &= \left(-\frac{1}{2}(t_i - y(x_i, W))^T \Sigma^{-1} (t_i - y(x_i, W)) \right) - \log \sqrt{(2\pi)^K \det \Sigma} = \end{aligned}$$

$$\begin{aligned} &= \left(-\frac{1}{2}(t_i - y(x_i, W))^T \Sigma^{-1} (t_i - y(x_i, W)) \right) - \frac{1}{2} \log((2\pi)^K \det \Sigma) = \\ &= \left(-\frac{1}{2}(t_i - y(x_i, W))^T \Sigma^{-1} (t_i - y(x_i, W)) \right) - \frac{K}{2} \log(2\pi) - \frac{1}{2} \log \det \Sigma = \\ &= -\frac{1}{2}((t_i - y(x_i, W))^T \Sigma^{-1} (t_i - y(x_i, W))) + K \log 2\pi + \log \det \Sigma \end{aligned}$$

Now that we have the log-likelihood for each target, we can compute the log-likelihood for all N independent observations. It will turn out to be a sum of log terms, since we can multiply the likelihoods for all the independent observations. So we have:

$$p(T|W, \Sigma) = \prod_{i=1}^N N(t_i | y(x_i, W), \Sigma)$$

$$\log p(T|W, \Sigma) = \sum_{i=1}^N \log N(t_i | y(x_i, W), \Sigma) =$$

And now using the previous results:

$$\begin{aligned} &= \sum_{i=1}^N -\frac{1}{2}((t_i - y(x_i, W))^T \Sigma^{-1}(t_i - y(x_i, W)) + K \log 2\pi + \log \det \Sigma) = \\ &= -\frac{1}{2}(NK \log 2\pi + N \log \det \Sigma + \sum_{i=1}^N (t_i - y(x_i, W))^T \Sigma^{-1}(t_i - y(x_i, W))) \end{aligned}$$

So the log-likelihood of T is given by $\log p(T|W, \Sigma) = -\frac{1}{2}(NK \log 2\pi + N \log \det \Sigma + \sum_{i=1}^N (t_i - y(x_i, W))^T \Sigma^{-1}(t_i - y(x_i, W)))$.