

PML hw3 Theory:

● Q1:^(a) We have

•) $\log \tilde{p}(x|a,b) = (a-1) \log x - bx$

$\partial_x \log \tilde{p}(x|a,b) = \frac{a-1}{x} - b$... setting equal to zero gives mode
 $\hat{x} = \frac{a-1}{b}$

$\partial_x^2 \log \tilde{p}(x|a,b) \big|_{x=\hat{x}} = -\frac{a-1}{\hat{x}^2} = -\frac{a-1}{\left(\frac{a-1}{b}\right)^2} = -\frac{b^2}{a-1} =: \psi$

● The Taylor approximation around \hat{x} is given by:

$\log \tilde{p}(x|a,b) \cong \log \tilde{p}(\hat{x}|a,b) - \frac{1}{2} \left(\frac{b^2}{a-1} \right) (x-\hat{x})^2$
 $\Rightarrow \tilde{p}(x|a,b) = \tilde{p}(\hat{x}|a,b) \exp\left(-\frac{1}{2} \frac{(x-\hat{x})^2}{\frac{a-1}{b^2}}\right)$

We can actually remove the \sim from p since $\partial_x p = \partial_x \tilde{p}$

So $p(x|a,b) \cong \tilde{p}(\hat{x}|a,b) \exp\left(-\frac{1}{2} \frac{(x-\hat{x})^2}{\frac{a-1}{b^2}}\right)$ (*)

which we recognize as the functional form of a normal distribution w/ mean $\frac{a-1}{b}$ and variance $\frac{a-1}{b^2}$

● •) Let $b=1$

from our expression (*), we then have

$\int_{\mathbb{R}} p(x|a,b) \cong p(\hat{x}|a,b) \int_{\mathbb{R}} \exp\left(-\frac{1}{2} \frac{(x-\hat{x})^2}{\frac{a-1}{b^2}}\right) dx \cong 1$ (since p is a pdf)

$\Rightarrow 1 \cong \frac{1^a}{\Gamma(a)} \left(\frac{a-1}{1}\right)^{a-1} e^{-(a-1)} \int_{-\infty}^{+\infty} \exp\left(-\frac{(x-\frac{a-1}{1})^2}{2(a-1)}\right) dx$

$\Rightarrow \Gamma(a) \cong (a-1)^{a-1} e^{-(a-1)} \int_{-\infty}^{+\infty} \exp\left(-\frac{(x-(a-1))^2}{2(a-1)}\right) dx$

$= (a-1)^{a-1} e^{-(a-1)} \sqrt{2\pi(a-1)}$

(recognizing the Gaussian Integral)

(b) we consider the product of the Gaussian Likelihood & Wishart prior & show that it also takes the form of a Wishart distribution (unnormalized) ...

we have:

$$\left(\prod_{i=1}^n p(\underline{x}_i | \Sigma^{-1}) \right) p(\Sigma^{-1} | W, \nu)$$

~~$$\frac{1}{(2\pi)^{d/2}} \exp\left(-\frac{1}{2}(\underline{x}_i - \underline{\mu})^T \Sigma^{-1} (\underline{x}_i - \underline{\mu})\right)$$~~

$$= \left(\frac{1}{(2\pi)^{d/2}} |\Sigma^{-1}|^{1/2} \right)^n \exp\left(-\frac{1}{2} \sum_{i=1}^n (\underline{x}_i - \underline{\mu})^T \Sigma^{-1} (\underline{x}_i - \underline{\mu})\right) \frac{|\Sigma^{-1}|^{\frac{\nu-d-1}{2}} \exp\left(-\frac{1}{2} \text{tr}(W^{-1} \Sigma^{-1})\right)}{2^{\frac{d\nu}{2}} |W|^{\nu/2} \Gamma_d\left(\frac{\nu}{2}\right)}$$

$$\propto |\Sigma^{-1}|^{\frac{\nu-d+n-1}{2}} \exp\left(-\frac{1}{2} \left[\sum_{i=1}^n (\underline{x}_i - \underline{\mu})^T \Sigma^{-1} (\underline{x}_i - \underline{\mu}) + \text{tr}(W^{-1} \Sigma^{-1}) \right]\right)$$

we now make use of the following useful trace identities:

• $v^T \Omega v = \text{tr}(\Omega v v^T) = \text{tr}(v v^T \Omega)$ $\forall v \in \mathbb{R}^n, \Omega \in \text{Mat}_{n \times n}(\mathbb{R})$

Thus $\forall i \in \{1, \dots, n\}$; we have $(\underline{x}_i - \underline{\mu})^T \Sigma^{-1} (\underline{x}_i - \underline{\mu}) = \text{tr}((\underline{x}_i - \underline{\mu})^T (\underline{x}_i - \underline{\mu}) \Sigma^{-1})$
(as Σ^{-1} is symmetric)

since the sum of traces is the trace of a sum we have:

$$\sum_{i=1}^n (\underline{x}_i - \underline{\mu})^T \Sigma^{-1} (\underline{x}_i - \underline{\mu}) = \text{tr}\left(\sum_{i=1}^n (\underline{x}_i - \underline{\mu})^T (\underline{x}_i - \underline{\mu}) \Sigma^{-1}\right)$$

therefore:

$$\begin{aligned} \left(\prod_{i=1}^n p(\underline{x}_i | \Sigma^{-1}) \right) p(\Sigma^{-1} | W, \nu) &\propto |\Sigma^{-1}|^{\frac{\nu-d+n-1}{2}} \exp\left(-\frac{1}{2} \left[\text{tr}(W^{-1} \Sigma^{-1}) + \sum_{i=1}^n (\underline{x}_i - \underline{\mu})^T (\underline{x}_i - \underline{\mu}) \Sigma^{-1} \right]\right) \\ &= |\Sigma^{-1}|^{\frac{\nu-d+n-1}{2}} \exp\left[-\frac{1}{2} \text{tr}\left((W^{-1} + \sum_{i=1}^n (\underline{x}_i - \underline{\mu})^T (\underline{x}_i - \underline{\mu}) \mathbb{I}) \Sigma^{-1}\right)\right] \end{aligned}$$

which we recognize as the functional form of the Wishart distribution

where the Wishart prior is the conjugate prior for Σ^{-1} and the posterior parameters are as above