

2)

$$p(x|a,b) = q(x;a,b) = \frac{b^a}{\Gamma(a)} x^{a-1} e^{-bx} \quad \text{with } \Gamma(a) = \int_0^{\infty} t^{a-1} e^{-t} dt$$

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

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

$$\frac{\partial \log \tilde{p}}{\partial x} = \frac{a-1}{x} - b = 0 \Rightarrow a-1 = bx \Rightarrow x^* = \frac{a-1}{b} = \hat{x}(\text{mode})$$

$$\left. \frac{\partial^2 \log \tilde{p}}{\partial x^2} \right|_{x=x^*} = \left. \frac{1-a}{x^2} \right|_{x=x^*} = \frac{(1-a)b^2}{(a-1)^2} = -\frac{b^2}{a-1} \quad \text{and } \sigma^2 = \frac{a-1}{b^2} \text{ thus}$$

Finally $\underbrace{q(x|a,b)}_{\text{approximation}} = N(x; \frac{a-1}{b}, \frac{a-1}{b^2}) = \frac{b e^{-\frac{b^2(x-\frac{a-1}{b})^2}{2(a-1)}}}{\sqrt{2\pi(a-1)}}$

For $b=1$, $q(x|a,b) = N(x; a-1, a-1) = \frac{\exp[-\frac{(x-a+1)^2}{2(a-1)}]}{\sqrt{2\pi(a-1)}}$

To find Stirling approximation:

We know that $\Gamma(a) = \int_0^{\infty} x^{a-1} e^{-x} dx = (a-1)!$

we also know $\int p(x|a,b) \approx p(\hat{x}) \int \exp\left[-\frac{(x-\hat{x})^2}{2\sigma^2}\right] dx = 1$

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$$1 \approx \frac{\hat{x}^{a-1} e^{-\hat{x}}}{\Gamma(a)} \int \exp\left[-\frac{(x-\hat{x})^2}{2(a-1)}\right] dx$$

$$\Gamma(n+1) \approx \sqrt{2\pi n} \left(\frac{n}{e}\right)^n$$

Q.E.D.

$$1 \approx \frac{(a-1)^{a-1} e^{-(a-1)}}{\Gamma(a)} \sqrt{2\pi(a-1)}$$

$$\Gamma(a) \approx (a-1)^{a-1} e^{-(a-1)} \sqrt{2\pi(a-1)} = \sqrt{2\pi(a-1)} \left(\frac{a-1}{e}\right)^{a-1}$$

$$b) \quad W(x_i | \mu, \Sigma) = \frac{|\Sigma^{-1}|^{\frac{1}{2}}}{(2\pi)^{\frac{d}{2}}} \exp \left[-\frac{(x_i - \mu)^T \Sigma^{-1} (x_i - \mu)}{2} \right] = p(x_i | \mu, \Sigma) \quad (\text{or use } p(x_i | \mu, \Sigma^{-1}))$$

show conjugate prior under this likelihood:

$$p(\Sigma^{-1} | W, v) = W(\Sigma^{-1} | W, v) = \frac{|\Sigma^{-1}|^{(v-d-1)/2} \exp(-\frac{\text{tr}(W \Sigma^{-1})}{2})}{2^{dv/2} |W|^{v/2} \Gamma_d(v/2)}$$

Where tr is the trace and $\Gamma_d = \pi^{d(d-1)/4} \prod_{i=1}^d \Gamma(\frac{d-i+1}{2})$

We need to prove that the posterior distribution of Σ^{-1} after observing data $\{x_i\}$ is also in the same distributional family as the prior. In other words

$$\underbrace{p(\Sigma^{-1} | W, v, X)}_{\text{Wishart}} \propto \underbrace{p(x_i | \mu, \Sigma^{-1})}_{\text{Wishart}} \underbrace{p(\Sigma^{-1} | W, v)}_{\text{Wishart}}$$

$$\propto \underbrace{\prod_i p(x_i | \mu, \Sigma^{-1})}_{\text{By i.i.d. assumption}} p(\Sigma^{-1} | W, v)$$

It is also a Gaussian

Using the property for positive definite square matrix Σ^{-1} :

$$(x_i - \mu)^T \Sigma^{-1} (x_i - \mu) = \text{tr}((x_i - \mu)(x_i - \mu)^T \Sigma^{-1})$$

For the multiplication of i.i.d. Gaussians this takes the form:

$$\prod_{i=1}^n A_i \exp[-\text{tr}((x_i - \mu)(x_i - \mu)^T \Sigma^{-1})/2] = B \exp[-\frac{1}{2} \text{tr}(\sum_{i=1}^n (x_i - \mu)(x_i - \mu)^T \Sigma^{-1})]$$

Finally multiplying the exponentials of the combined Gaussians and the Wishart prior, we have

$$\begin{aligned}
 p(\Sigma^{-1} | W^t, v^t, X) &\propto \prod_{i=1}^n p(x_i | \mu, \Sigma^{-1}) p(\Sigma^{-1} | W, v) \\
 &\propto \frac{|\Sigma^{-1}|^n}{(2\pi)^{\frac{nd}{2}}} \exp\left[-\text{tr}\left(\left(\sum_{i=1}^n (x_i - \mu)(x_i - \mu)^T\right) \Sigma^{-1} / 2\right)\right] \\
 &\quad \times \frac{|\Sigma^{-1}|^{(v-d-1)/2}}{2^{vd/2} |W|^{v/2} \Gamma(v/2)} \exp\left[\text{tr}(W^{-1} \Sigma^{-1})\right] \\
 &\propto \frac{|\Sigma^{-1}|^{(v+n-d-1)/2}}{2^{(v+n)/2} C} \exp\left[-\text{tr}\left(\left(W^{-1} + \sum_{i=1}^n (x_i - \mu)(x_i - \mu)^T\right) \Sigma^{-1} / 2\right)\right]
 \end{aligned}$$

where C denotes normalization constant. From this we clearly see that the posterior takes the form:

$$\begin{aligned}
 p(\Sigma^{-1} | W', v', X) &= p(\Sigma^{-1} | (W^{-1} + \sum_{i=1}^n (x_i - \mu)(x_i - \mu)^T)^{-1}, v+n) \\
 &= \text{Wishart}(\Sigma^{-1} | (W^{-1} + \sum_{i=1}^n (x_i - \mu)(x_i - \mu)^T)^{-1}, v+n)
 \end{aligned}$$

Q.E.D

See also: Normal Wishart Distribution