

# 1 Wishart Distribution

a  $p \times p$  Wishart random variate has a density of the form

$$\mathcal{W}(\Omega | V, k) = C(k, V) |\Omega|^{(k-p-1)/2} \exp\left(-\frac{1}{2} \text{Tr}(V^{-1}\Omega)\right) \quad (1)$$

$$C(k, V) = |V|^{-k/2} \left( 2^{kp/2} \pi^{p(p-1)/4} \prod_{i=1}^p \Gamma\left(\frac{k+1-i}{2}\right) \right)^{-1} \quad (2)$$

The log-density is

$$\log \mathcal{W}(\Omega | k, V) = \frac{k-p-1}{2} \log |\Omega| - \frac{1}{2} \text{Tr}(V^{-1}\Omega) - \frac{k}{2} \log |V| \quad (3)$$

$$- \frac{kp}{2} \log 2 - \frac{p(p-1)}{4} \log \pi - \sum_{i=1}^p \log \Gamma\left(\frac{k+1-i}{2}\right) \quad (4)$$

Before jumping into the derivative of the log-density, let's do it by parts.

- $\ell = \text{Tr}(V^{-1}\Omega) = \text{vec}(\Omega)' \text{vec}(V^{-1})$

$$d\ell = \text{vec}(\Omega)' \text{vec}(dV^{-1}) \quad (5)$$

$$= \text{vec}(\Omega)' \text{vec}(-V^{-1} dV V^{-1}) \quad (6)$$

$$= -\text{vec}(\Omega)' (V^{-1} \otimes V^{-1}) D_p d \text{vech}(V) \quad (7)$$

$$\frac{d \text{Tr}(V^{-1}\Omega)}{d \text{vech}(V)'} = -D_p' (V^{-1} \otimes V^{-1}) D_p \text{vech}(\Omega) \quad (8)$$

where  $D_p$  is the unique duplication matrix such that  $D_p \text{vech}(A) = \text{vec}(A)$ .

- $\ell = \log |V|$

$$\frac{d \log |V|}{d \text{vech}(V)'} = D_p \text{vech}(V^{-1}) \quad (9)$$

Therefore,

$$\nabla_{\text{vech}(V)} \log \mathcal{W}(\Omega | k, V) = \frac{1}{2} D_p' (V^{-1} \otimes V^{-1}) D_p \text{vech}(\Omega) - \frac{k}{2} \text{vech}(V^{-1}) \quad (10)$$

$$\nabla_k \log \mathcal{W}(\Omega | k, V) = \frac{1}{2} \log |\Omega| - \frac{1}{2} \log |V| - \frac{p}{2} \log 2 - \frac{1}{2} \sum_{i=1}^p \psi\left(\frac{k+1-i}{2}\right) \quad (11)$$

## 1.1 Fisher Information of Wishart

To get the Fisher information matrix, we need to go through quite a few steps. First, according to [1],

- $(\text{Var}(\text{vec}(\Omega)))$

$$\text{Var}(\text{vec}(\Omega)) = k (\mathbf{I}_{p^2} + K_{pp}) (V \otimes V) \quad (12)$$

where  $K_{pp}$  is a  $p^2 \times p^2$  commutation matrix such that

$$K_{pp} \text{vec}(C) = \text{vec}(C') \quad (13)$$

for a  $p \times p$  matrix  $C$ .

- $(\text{Var}(\log |\Omega|))$  To get the variance of the log-determinant, we will rely on the following relation.

$$\frac{|\Omega|}{|V|} = \chi_k^2 \chi_{k-1}^2 \cdots \chi_{k-p+1}^2 \quad (14)$$

where every chi-squared random variables are independent of each other. We need to do variable transformation to get the density of log chi-squared random variate. If we say  $X \sim \log \chi_v^2$ , the density is

$$p(x) = \left(2^{v/2} \Gamma(v/2)\right)^{-1} \exp\left(\frac{1}{2}vx - \frac{1}{2}\exp(x)\right), \quad -\infty < x < \infty \quad (15)$$

Then, performing the integration, we obtain the following central moments

$$\mathbf{E}(X) = \log 2 + \psi(v/2) \quad (16)$$

$$\text{Var}(X) = \psi_1(v/2) \quad (17)$$

where  $\psi_1$  is the tri-gamma function. Thus, since  $\log |\Omega| - \log |V| = \sum_{i=1}^p \log \chi_{k-i+1}^2$ ,

$$\text{Var}(\log |\Omega|) = \sum_{i=1}^p \psi_1\left(\frac{k-i+1}{2}\right) \quad (18)$$

- The block-diagonal matrices of the Fisher information have been obtained in the above items. However, it is quite difficult to compute the following off-diagonal covariance term:

$$\text{Cov}(\text{vec}(\Omega), \log |\Omega|) \quad (19)$$

## 2 SUR

Seemingly Unrelated Regression model is constructed as follows.

$$\mathbf{y}_t = X_t' \beta + \mathbf{e}_t, \quad \mathbf{e}_t \sim \mathcal{N}(\mathbf{0}, \Omega^{-1}) \quad (20)$$

- $\beta \sim \mathcal{N}(\mu_\beta^0, \Sigma_\beta^0), \quad (m \times 1)$
- $\Omega \sim \mathcal{W}(k, V), \quad (p \times p)$

The varational posteriors are

- $q(\beta) = \mathcal{N}(\mu_\beta^q, \Sigma_\beta^q)$
- $q(\Omega) = \mathcal{W}(k_q, V_q)$

Therefore,

$$\log h(\theta) = \frac{T}{2} \log \det \Omega - \frac{1}{2} \sum_{t=1}^T (\mathbf{y}_t - X_t' \beta)' \Omega (\mathbf{y}_t - X_t' \beta) - \frac{Tp}{2} \log(2\pi) \quad (21)$$

$$- \frac{1}{2} \log \det \Sigma_\beta^0 - \frac{1}{2} (\beta - \mu_\beta^0)' \Sigma_\beta^{0^{-1}} (\beta - \mu_\beta^0) \quad (22)$$

$$+ \frac{k-p-1}{2} \log \det \Omega - \frac{1}{2} \text{Tr}(V^{-1} \Omega) - \frac{k}{2} \log \det V - \frac{kp}{2} \log 2 \quad (23)$$

$$- \sum_{i=1}^p \log \Gamma\left(\frac{k+1-i}{2}\right) \quad (24)$$

$$\log q_\lambda(\theta) = -\frac{1}{2} \log \det \Sigma_\beta^q - \frac{1}{2} (\beta - \mu_\beta^q)' \Sigma_\beta^{q^{-1}} (\beta - \mu_\beta^q) \quad (25)$$

$$+ \frac{k_q-p-1}{2} \log \det \Omega - \frac{1}{2} \text{Tr}(V_q^{-1} \Omega) - \frac{k_q}{2} \log \det V_q - \frac{k_q p}{2} \log 2 \quad (26)$$

$$- \sum_{i=1}^p \log \Gamma\left(\frac{k_q+1-i}{2}\right) \quad (27)$$

where  $\theta = (\beta, \Omega)$  and  $\lambda = (\mu_\beta^q, \Sigma_\beta^q, k_q, V_q)$ .

## References

- [1] MUIRHEAD, R. J. *Aspects of multivariate statistical theory*. Wiley series in probability and mathematical statistics. Probability and mathematical statistics. John Wiley & Sons, New York, 1982.