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PS 2 | Stat 234

6.4.1 Obtain the pdf of $\mathbf{X} \sim \mathcal{N}_q^p(\mathbf{M}, \mathbf{A} \otimes \mathbf{B})$, where $\mathbf{A} > \mathbf{0}$ is in \mathbb{R}_p^p and $\mathbf{B} > \mathbf{0}$ is in \mathbb{R}_q^q :

$$f(\mathbf{X}) = (2\pi)^{-\frac{pq}{2}} |\mathbf{A}|^{-\frac{q}{2}} |\mathbf{B}|^{-\frac{p}{2}} \text{etr} \left[-\frac{1}{2} \mathbf{A}^{-1} (\mathbf{X} - \mathbf{M}) \mathbf{B}^{-1} (\mathbf{X} - \mathbf{M})^T \right] \quad (1)$$

where $\text{etr} = \exp(\text{tr}(\cdot))$.

Hint: Let $\mathbf{X} = \mathbf{A}^{\frac{1}{2}} \mathbf{Z} \mathbf{B}^{\frac{1}{2}} + \mathbf{M}$, where $\mathbf{Z} \sim \mathcal{N}_q^p(\mathbf{0}, \mathbf{I}_p \otimes \mathbf{I}_q)$, and use Corollary 6.1.

Proof. From the hint, let $\mathbf{Z} \sim \mathcal{N}_q^p(\mathbf{0}, \mathbf{I}_p \otimes \mathbf{I}_q)$. Now recall that the Multivariate Gaussian distribution for $\mathbf{Z} \sim \mathcal{N}_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ we have

$$f(\mathbf{X}) = \frac{1}{(2\pi)^{\frac{p}{2}} |\boldsymbol{\Sigma}|^{\frac{1}{2}}} \exp \left[-\frac{1}{2} (\mathbf{X} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{X} - \boldsymbol{\mu}) \right] \quad (2)$$

$$= \frac{1}{(2\pi)^{\frac{p}{2}} |\boldsymbol{\Sigma}|^{\frac{1}{2}}} \text{etr} \left[-\frac{1}{2} (\mathbf{X} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{X} - \boldsymbol{\mu}) \right]. \quad (3)$$

Since the factors in the exponential function returns a constant, then we can apply the trace function. So that if $\mathbf{Z} \sim \mathcal{N}_q^p(\mathbf{0}, \mathbf{I}_p \otimes \mathbf{I}_q)$ then this is equivalent to $\text{vec}(\mathbf{Z}^T) \sim \mathcal{N}_{pq}(\text{vec}(\mathbf{0}^T), \mathbf{I}_p \otimes \mathbf{I}_q)$ or mathematically equivalent to:

$$f(\mathbf{Z}) = \frac{1}{(2\pi)^{\frac{pq}{2}} |\mathbf{I}_p \otimes \mathbf{I}_q|^{\frac{1}{2}}} \text{etr} \left[-\frac{1}{2} \mathbf{Z}^T (\mathbf{I}_p \otimes \mathbf{I}_q)^{-1} \mathbf{Z} \right] \quad (4)$$

$$= \frac{1}{(2\pi)^{\frac{pq}{2}}} \text{etr} \left[-\frac{1}{2} \mathbf{Z}^T \mathbf{Z} \right] \quad (5)$$

Now consider the following transformations $\mathbf{X} = \mathbf{A}^{\frac{1}{2}} \mathbf{Z} \mathbf{B}^{\frac{1}{2}} + \mathbf{M}$, then $\mathbf{X} - \mathbf{M} = \mathbf{A}^{\frac{1}{2}} \mathbf{Z} \mathbf{B}^{\frac{1}{2}}$, and since $\mathbf{A} \in \mathcal{P}_p$ and $\mathbf{B} \in \mathcal{P}_q$. Then both \mathbf{A} and \mathbf{B} are nonsingular. So that, $\mathbf{A}^{-\frac{1}{2}} (\mathbf{X} - \mathbf{M}) \mathbf{B}^{-\frac{1}{2}} = \mathbf{Z}$. Using Corollary 6.1, $J(\mathbf{Z} \rightarrow \mathbf{X}) = |\mathbf{A}|^{-\frac{q}{2}} |\mathbf{B}|^{-\frac{p}{2}}$. So that substituting the terms into Equation (5), we have

$$\begin{aligned} f(\mathbf{X}) &= \frac{1}{(2\pi)^{\frac{pq}{2}}} \text{etr} \left[-\frac{1}{2} (\mathbf{A}^{-\frac{1}{2}} (\mathbf{X} - \mathbf{M}) \mathbf{B}^{-\frac{1}{2}})^T (\mathbf{A}^{-\frac{1}{2}} (\mathbf{X} - \mathbf{M}) \mathbf{B}^{-\frac{1}{2}}) \right] |J(\mathbf{Z} \rightarrow \mathbf{X})| \\ &= \frac{1}{(2\pi)^{\frac{pq}{2}}} |\mathbf{A}|^{-\frac{q}{2}} |\mathbf{B}|^{-\frac{p}{2}} \text{etr} \left[-\frac{1}{2} (\mathbf{B}^{-\frac{1}{2}} (\mathbf{X} - \mathbf{M})^T \mathbf{A}^{-\frac{1}{2}}) (\mathbf{A}^{-\frac{1}{2}} (\mathbf{X} - \mathbf{M}) \mathbf{B}^{-\frac{1}{2}}) \right] \\ &= \frac{1}{(2\pi)^{\frac{pq}{2}}} |\mathbf{A}|^{-\frac{q}{2}} |\mathbf{B}|^{-\frac{p}{2}} \text{etr} \left[-\frac{1}{2} (\mathbf{B}^{-\frac{1}{2}} (\mathbf{X} - \mathbf{M})^T \mathbf{A}^{-1} (\mathbf{X} - \mathbf{M}) \mathbf{B}^{-\frac{1}{2}}) \right]. \end{aligned}$$

And since trace is invariant under circular permutation, then

$$\begin{aligned} f(\mathbf{X}) &= \frac{1}{(2\pi)^{\frac{pq}{2}}} |\mathbf{A}|^{-\frac{q}{2}} |\mathbf{B}|^{-\frac{p}{2}} \text{etr} \left[-\frac{1}{2} \mathbf{B}^{-\frac{1}{2}} \mathbf{B}^{-\frac{1}{2}} (\mathbf{X} - \mathbf{M})^T \mathbf{A}^{-1} (\mathbf{X} - \mathbf{M}) \right] \\ &= \frac{1}{(2\pi)^{\frac{pq}{2}}} |\mathbf{A}|^{-\frac{q}{2}} |\mathbf{B}|^{-\frac{p}{2}} \text{etr} \left[-\frac{1}{2} \mathbf{B}^{-1} (\mathbf{X} - \mathbf{M})^T \mathbf{A}^{-1} (\mathbf{X} - \mathbf{M}) \right] \\ &= \frac{1}{(2\pi)^{\frac{pq}{2}}} |\mathbf{A}|^{-\frac{q}{2}} |\mathbf{B}|^{-\frac{p}{2}} \text{etr} \left[-\frac{1}{2} (\mathbf{X} - \mathbf{M}) \mathbf{B}^{-1} (\mathbf{X} - \mathbf{M})^T \mathbf{A}^{-1} \right] \\ &= (2\pi)^{-\frac{pq}{2}} |\mathbf{A}|^{-\frac{q}{2}} |\mathbf{B}|^{-\frac{p}{2}} \text{etr} \left[-\frac{1}{2} \mathbf{A}^{-1} (\mathbf{X} - \mathbf{M}) \mathbf{B}^{-1} (\mathbf{X} - \mathbf{M})^T \right]. \end{aligned}$$

□

6.4.8 Assume $(x_i, y_i)^T, i = 1, \dots, n$ are i.i.d.

$$\begin{pmatrix} x \\ y \end{pmatrix} \sim \mathcal{N}_2 \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right) \quad (6)$$

and let r be the sample correlation coefficient. Prove the asymptotic result $\sqrt{n}(r - \rho) \xrightarrow{d} \mathcal{N}(0, (1 - \rho^2)^2)$.

Proof. Let $\mathbf{v} = \begin{pmatrix} x \\ y \end{pmatrix}$, then recall that the MGF of $M_{\mathbf{v}}(t) = \exp \left(\frac{1}{2} \mathbf{t}^T \boldsymbol{\Sigma} \mathbf{t} + \mathbf{t}^T \boldsymbol{\mu} \right) = \exp \left(\frac{1}{2} \mathbf{t}^T \boldsymbol{\Sigma} \mathbf{t} \right)$. Now let $\mathbf{t} = \begin{pmatrix} t_1 \\ t_2 \end{pmatrix}, \boldsymbol{\Sigma} =$

$\begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$. Then,

$$\mathbf{t}^T \Sigma \mathbf{t} = [t_1 \quad t_2] \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \begin{bmatrix} t_1 \\ t_2 \end{bmatrix} = t_1^2 + \rho t_1 t_2 + \rho t_1 t_2 + t_2^2$$

So that $\exp(\frac{1}{2} \mathbf{t}^T \Sigma \mathbf{t}) = \exp(\frac{1}{2} t_1^2 + \rho t_1 t_2 + \frac{1}{2} t_2^2)$. Now from Example 6.4, note that

$$\sqrt{n} \left[\begin{pmatrix} s_1^2 \\ s_{12} \\ s_2^2 \end{pmatrix} - \begin{pmatrix} \sigma_1^2 \\ \sigma_{12} \\ \sigma_2^2 \end{pmatrix} \right] \xrightarrow{d} \mathcal{N}_3(0, \Omega) \quad (7)$$

where

$$\Omega = \begin{pmatrix} \mu_4^1 - (\mu_2^1)^2 & \mu_{31}^{12} - \mu_{11}^{12} \mu_2^1 & \mu_{22}^{12} - \mu_2^1 \mu_2^2 \\ \cdot & \mu_{22}^{12} - (\mu_{11}^{12})^2 & \mu_{13}^{12} - \mu_{11}^{12} \mu_2^2 \\ \cdot & \cdot & \mu_4^2 - (\mu_2^2)^2 \end{pmatrix} \quad (8)$$

Next is to compute for the values of the components of Ω , and from the problem $\mu_1 = \mu_2 = 0$ and $\sigma_1^2 = \sigma_2^2 = 1$. Thus

$$\begin{aligned} \mu_4^1 &= \mathbb{E}(x - \mu_1)^4 = \mathbb{E}x^4 \\ \mu_2^1 &= \mathbb{E}(x - \mu_1)^2 = \sigma_1^2 = 1 \\ \mu_{31}^{12} &= \mathbb{E}(x - \mu_1)^3(y - \mu_2) = \mathbb{E}x_1^3 x_2 \\ \mu_{11}^{12} &= \mathbb{E}(x - \mu_1)(y - \mu_2) = \sigma_{12} \\ \mu_2^2 &= \mathbb{E}(y - \mu_2)^2 = \sigma_2^2 = 1 \\ \mu_{22}^{12} &= \mathbb{E}(x - \mu_1)^2(y - \mu_2)^2 = \mathbb{E}x^2 y^2 \\ \mu_{13}^{12} &= \mathbb{E}(x - \mu_1)(y - \mu_2)^3 = \mathbb{E}xy^3 \\ \mu_4^2 &= \mathbb{E}(y - \mu_2)^4 = \mathbb{E}y^4 \end{aligned}$$

To avoid confusion, we stressed that t_1 is for x and t_2 is for y . So that

(a) $\mathbb{E}x^4 = \frac{\partial^4}{\partial t_1^4} M_{\mathbf{v}}(t_1, t_2) \Big|_{t_1=t_2=0}$, and let $u = \frac{1}{2} t_1^2 + \rho t_1 t_2 + \frac{1}{2} t_2^2$, then $\frac{\partial}{\partial t_1} u = t_1 + \rho t_2$, and $f = \exp(u)$. Thus,

$$\begin{aligned} f' &= (t_1 + \rho t_2) \exp(u) \\ f'' &= \exp(u) + (t_1 + \rho t_2)^2 \exp(u) \\ f''' &= (t_1 + \rho t_2) \exp(u) + 2(t_1 + \rho t_2)(1) \exp(u) + (t_1 + \rho t_2)^3 \exp(u) \\ f'''' &= \exp(u) + (t_1 + \rho t_2)^2 \exp(u) + 2(1) \exp(u) + 2(t_1 + \rho t_2)^2 \exp(u) \\ &\quad + 3(t_1 + \rho t_2)^2 \exp(u) + (t_1 + \rho t_2)^4 \exp(u) \end{aligned}$$

If $t_1 = t_2 = 0$, then $u|_{t_1=t_2=0} = \frac{1}{2}(0)^2 + \rho(0) + \frac{1}{2}(0)^2 = 0$. Implies that,

$$f''''|_{t_1=t_2=0} = 1 + 0 + 2 + 0 + 0 = 3. \quad (9)$$

(b) $\mu_{31}^{12} = \mathbb{E}x^3 y = \frac{\partial^4}{(\partial t_1)^3 \partial t_2} M_{[x \ y]^T}(t_1, t_2) \Big|_{t_1=t_2=0}$. Now let $u = \frac{1}{2} t_1^2 + \rho t_1 t_2 + \frac{1}{2} t_2^2$, and $a = \frac{\partial u}{\partial t_1} = t_1 + \rho t_2$; $b = \frac{\partial u}{\partial t_2} = \rho t_1 + t_2$.

$$\begin{aligned} \frac{\partial}{(\partial t_1)^3 \partial t_2} \exp(u) &= \frac{\partial}{(\partial t_1)^3} \exp(u) (\rho t_1 + t_2) \\ &= \frac{\partial}{(\partial t_1)^2} [(t_1 + \rho t_2) \exp(u) (\rho t_1 + t_2) + \exp(u) \rho] \\ &= \frac{\partial}{(\partial t_1)^2} [(\rho t_1^2 + t_1 t_2 + \rho^2 t_1 t_2 + \rho t_2^2) \exp(u) \\ &\quad + \exp(u) \rho] \\ &= \rho \exp(u) (t_1 + \rho t_2)^2 + \rho \exp(u) \\ &\quad + (\rho t_1^3 + 2\rho^2 t_1 t_2 + \rho^3 t_1 t_2^2 + t_1^2 t_2 + 2\rho t_1 t_2^2 + \rho^2 t_2^3) \\ &\quad \times \exp(u) (t_1 + \rho t_2) + \exp(u) \\ &\quad \times (3\rho t^2 + 4\rho^2 t_1 t_2 + \rho^3 t_2^2 + 2t_1 t_2 + \rho t_2^2) \\ &\quad + (2\rho t_1 + \rho^2 t_2 + t_2) \exp(u) (t_1 + \rho t_2) + \exp(u) (2\rho) \end{aligned} \quad (10)$$

Substituting $t_1 = t_2 = 0$ to above expression returns:

$$\frac{\partial}{(\partial t_1)^3 \partial t_2} \exp(u) \Big|_{t_1=t_2=0} = 3\rho. \quad (11)$$

(c) $\mu_{11}^{12} = \mathbb{E}(x - \mu_1)(y - \mu_2) = \sigma_{12}$. It follows from Equation (10)

$$\frac{\partial}{\partial t_1 \partial t_2} \exp(u) = (t_1 + \rho t_2) \exp(u) (\rho t_1 + t_2) + \exp(u) \rho \quad (12)$$

So that,

$$\frac{\partial}{\partial t_1 \partial t_2} \exp(u) \Big|_{t_1=t_2=0} = \rho \quad (13)$$

(d) $\mu_{22}^{12} = \mathbb{E}x^2y^2 = \frac{\partial}{(\partial t_1)^2(\partial t_2)^2} M_{[x \ y]}(t_1, t_2) \Big|_{t_1=t_2=0}$. Thus,

$$\begin{aligned} \mu_{22}^{12} &= \frac{\partial^2}{(\partial t_1)^2} \frac{\partial}{\partial t_2} [\exp(u)(\rho t_1 + t_2)] \\ &= \frac{\partial^2}{(\partial t_1)^2} [\exp(u) + (\rho t_1 + t_2)^2 \exp(u)] \\ &= \frac{\partial}{\partial t_1} [\exp(u)(t_1 + \rho t_2) + (\rho t_1 + t_2)^2 \exp(u)] \\ &= \exp(u)(1) + (t_1 + \rho t_2) \exp(u)(t_1 + \rho t_2) \\ &\quad + (\rho t_1 + t_2)^2 [\exp(u)(1) + (t_1 + \rho t_2) \exp(u)(t_1 + \rho t_2)] \\ &\quad + 2\rho(\rho t_1 + t_2) \exp(u)(t_1 + \rho t_2) \\ &\quad + \exp(u)(t_1 + \rho t_2)2(\rho t_1 + t_2)\rho + \exp(u)2\rho^2 \end{aligned}$$

Therefore,

$$\frac{\partial}{(\partial t_1)^2(\partial t_2)^2} M_{[x \ y]}(t_1, t_2) \Big|_{t_1=t_2=0} = 1 + 2\rho^2. \quad (14)$$

Applying the same process we obtain $\mu_4^1 = 3 = \mu_4^2$ and $\mu_{31}^{12} = 3\rho = \mu_{13}^{12}$. Thus,

$$\begin{aligned} \mu_4^1 &= 3; \quad \mu_2^1 = 1 \\ \mu_{31}^{12} &= 3\rho; \quad \mu_{11}^{12} = \rho \\ \mu_2^2 &= 1; \quad \mu_{22}^{12} = 1 + 2\rho^2 \\ \mu_{13}^{12} &= 3\rho; \quad \mu_4^2 = 3. \end{aligned}$$

Therefore,

$$\begin{aligned} \Omega &= \begin{pmatrix} \mu_4^1 - (\mu_2^1)^2 & \mu_{31}^{12} - \mu_{11}^{12}\mu_2^1 & \mu_{22}^{12} - \mu_2^1\mu_2^2 \\ \cdot & \mu_{22}^{12} - (\mu_{11}^{12})^2 & \mu_{13}^{12} - \mu_{11}^{12}\mu_2^2 \\ \cdot & \cdot & \mu_4^2 - (\mu_2^2)^2 \end{pmatrix} \\ &= \begin{pmatrix} 3 - 1 & 3\rho - \rho(1) & 1 + 2\rho^2 - 1 \\ 3\rho - \rho(1) & 1 + 2\rho^2 - \rho^2 & 3\rho - \rho \\ 1 + 2\rho^2 - 1 & 3\rho - \rho & 3 - 1 \end{pmatrix} \\ &= \begin{pmatrix} 2 & 2\rho & 2\rho^2 \\ 2\rho & 1 + \rho^2 & 2\rho \\ 2\rho^2 & 2\rho & 2 \end{pmatrix} \end{aligned}$$

By Delta Method, define $g : \mathbb{R}^3 \rightarrow \mathbb{R}^1$,

$$g(\cdot) = \frac{s_{12}}{\sqrt{s_1^2 s_2^2}} = r. \quad (15)$$

Thus,

$$\sqrt{n}(x_n - c) = \sqrt{n} \left(\begin{bmatrix} s_1^2 \\ s_{12} \\ s_2^2 \end{bmatrix} - \begin{bmatrix} \sigma_1^2 \\ \sigma_{12} \\ \sigma_2^2 \end{bmatrix} \right) \xrightarrow{d} \mathcal{N}_3(0, \Omega) \quad (16)$$

So that,

$$\sqrt{n}(g(x_n) - g(c)) = \sqrt{n}(r - \rho) \xrightarrow{d} \mathbf{D}g(c)\mathbf{Z}, \quad (17)$$

and

$$\mathbf{D}g(c)\mathcal{N}_3(0, \Omega) \sim \mathcal{N}_3(\mathbf{0}, \mathbf{D}g(c)^T \Omega \mathbf{D}g(c)) \quad (18)$$

$$\mathbf{D}g(c)^T = \mathbf{D} \left(\frac{\sigma_{12}}{\sqrt{\sigma_1^2 \sigma_2^2}} \right)^T = \begin{bmatrix} \frac{\partial g(c)}{\partial \sigma_1^2} & \frac{\partial g(c)}{\partial \sigma_{12}} & \frac{\partial g(c)}{\partial \sigma_2^2} \end{bmatrix} \quad (19)$$

But $\frac{\sigma_{12}}{\sqrt{\sigma_1^2 \sigma_2^2}} = \sigma_{12}(\sigma_1^2)^{-\frac{1}{2}}(\sigma_2^2)^{-\frac{1}{2}}$, then

$$\begin{aligned} \frac{\partial g(c)}{\partial \sigma_1^2} &= -\frac{1}{2}\sigma_{12}(\sigma_1^2)^{-\frac{3}{2}}(\sigma_2^2)^{-\frac{1}{2}} \\ \frac{\partial g(c)}{\partial \sigma_{12}} &= (\sigma_1^2)^{-\frac{1}{2}}(\sigma_2^2)^{-\frac{1}{2}} \\ \frac{\partial g(c)}{\partial \sigma_2^2} &= -\frac{1}{2}\sigma_{12}(\sigma_1^2)^{-\frac{1}{2}}(\sigma_2^2)^{-\frac{3}{2}} \end{aligned}$$

And using the fact that $\sigma_{12} = \rho$, $\sigma_1^2 = 1$, and $\sigma_2^2 = 1$. Then

$$\begin{aligned} \frac{\partial g(c)}{\partial \sigma_1^2} &= -\frac{\rho}{2} \\ \frac{\partial g(c)}{\partial \sigma_{12}} &= 1 \\ \frac{\partial g(c)}{\partial \sigma_2^2} &= -\frac{\rho}{2} \end{aligned}$$

Thus $\mathbf{Dg}(c)^T = \begin{bmatrix} -\frac{\rho}{2} & 1 & -\frac{\rho}{2} \end{bmatrix}$, so that

$$\begin{aligned} & \begin{bmatrix} -\frac{\rho}{2} & 1 & -\frac{\rho}{2} \end{bmatrix} \begin{pmatrix} 2 & 2\rho & 2\rho^2 \\ 2\rho & 1+\rho^2 & 2\rho \\ 2\rho^2 & 2\rho & 2 \end{pmatrix} \begin{bmatrix} -\frac{\rho}{2} \\ 1 \\ -\frac{\rho}{2} \end{bmatrix} \\ &= [\rho - \rho^3 \quad 1 - \rho^2 \quad \rho - \rho^3] \begin{bmatrix} -\frac{\rho}{2} \\ 1 \\ -\frac{\rho}{2} \end{bmatrix} \\ &= \left(-\frac{\rho(\rho - \rho^3)}{2} + 1 - \rho^2 - \frac{\rho(\rho - \rho^3)}{2} \right) = (-\rho(\rho - \rho^3) + 1 - \rho^2) \\ &= (\rho^4 - \rho^2 - \rho^2 + 1) \\ &= 1 - 2\rho^2 + \rho^4 = (1 - \rho^2)^2. \end{aligned}$$

Therefore,

$$\sqrt{n}(r - \rho) \xrightarrow{d} \mathcal{N}(0, (1 - \rho^2)^2). \quad (20)$$

□

7.5.5 Assume $\mathbf{W} \sim W_p(m)$, $m \geq p$ and $\mathbf{A} > \mathbf{0}$. Prove:

(a) $\mathbb{E}\mathbf{W} = m\mathbf{I}$

(b) $\mathbb{E}\mathbf{W}^{-1} = \mathbf{I}/(m - p - 1)$.

(a) *Proof.* Recall that $\mathbf{W} \sim W_p(m)$ iff $\sum_{i=1}^m \mathbf{z}_i \mathbf{z}_i^T \stackrel{d}{=} \mathbf{W}$, \mathbf{z}_i i.i.d. $\mathcal{N}(\mathbf{0}, \mathbf{I})$. Then using the fact that $\text{Cov}(\mathbf{z}_i, \mathbf{z}_i) = \mathbb{E}(\mathbf{z}_i \mathbf{z}_i^T) + \mathbb{E}\mathbf{z}_i \mathbb{E}\mathbf{z}_i^T = \text{Cov}(\mathbf{z}_i)$. So that $\mathbb{E}(\mathbf{z}_i \mathbf{z}_i^T) = \text{Cov}(\mathbf{z}_i) - \mathbb{E}\mathbf{z}_i \mathbb{E}\mathbf{z}_i^T = \mathbf{I} + \mathbf{0} = \mathbf{I}$. Therefore, $\sum_{i=1}^m \mathbf{z}_i \mathbf{z}_i^T = m\mathbf{I}$. □

(b) *Proof.* Consider the following Theorem,

Theorem 0.1. If $\mathbf{M} \sim W_p(n, \Sigma)$ and $\mathbf{a} \in \mathbb{R}^p$ and $n > p - 1$, then

$$\frac{\mathbf{a}^T \Sigma^{-1} \mathbf{a}}{\mathbf{a}^T \mathbf{M}^{-1} \mathbf{a}} \sim \chi_{n-p+1}^2. \quad (21)$$

Using the above Theorem suppose $\mathbf{W} \sim W_p(m, \mathbf{I})$ and $\mathbf{b} \in \mathbb{R}^p$, then

$$\begin{aligned} & \frac{\mathbf{b}^T \mathbf{I}^{-1} \mathbf{b}}{\mathbf{b}^T \mathbf{W}^{-1} \mathbf{b}} \sim \chi_{m-p+1}^2 \\ & \Rightarrow \left(\frac{\mathbf{b}^T \mathbf{I}^{-1} \mathbf{b}}{\mathbf{b}^T \mathbf{W}^{-1} \mathbf{b}} \right)^{-1} \sim \text{inverse } \chi_{(m-p+1)-2} \\ & = \frac{\mathbf{b}^T \mathbf{W}^{-1} \mathbf{b}}{\mathbf{b}^T \mathbf{I}^{-1} \mathbf{b}} \sim \text{inverse } \chi_{(m-p+1)-2}. \end{aligned}$$

So that,

$$\mathbb{E} \left[\frac{\mathbf{b}^T \mathbf{W}^{-1} \mathbf{b}}{\mathbf{b}^T \mathbf{I}^{-1} \mathbf{b}} \right] = \frac{1}{(m - p + 1) - 2}$$

Now $\mathbb{E} \left[\frac{\mathbf{b}^T \mathbf{W}^{-1} \mathbf{b}}{\mathbf{b}^T \mathbf{I}^{-1} \mathbf{b}} \right] = \frac{\mathbf{b}^T \mathbb{E}(\mathbf{W}^{-1}) \mathbf{b}}{\mathbf{b}^T \mathbf{b}} \Rightarrow \mathbf{b}^T \mathbb{E}(\mathbf{W}^{-1}) \mathbf{b} = \frac{\mathbf{b}^T \mathbf{I} \mathbf{b}}{(m-p+1)-2} = \frac{\mathbf{b}^T \mathbf{I} \mathbf{b}}{m-p-1}$. And because \mathbf{b} is arbitrary, then it follows that $\mathbb{E}\mathbf{W}^{-1} = \frac{\mathbf{I}}{m-p-1}$. □

7.5.7 Wishart Density

Obtain the p.d.f. of $\mathbf{V} \sim W_p(m, \Sigma)$, $m \geq p$, $\Sigma > \mathbf{0}$:

$$f_{\mathbf{V}}(\mathbf{V}) = \frac{1}{2^{mp/2} \Gamma_p(\frac{1}{2}m) |\Sigma|^{m/2}} |\mathbf{V}|^{(m-p-1)/2} \text{etr} \left(-\frac{1}{2} \Sigma^{-1} \mathbf{V} \right), \quad (22)$$

$\mathbf{V} > \mathbf{0}$.

Proof. From the definition of the Wishart distribution, $\mathbf{V} \sim W_p(m, \Sigma)$ iff $\mathbf{V} \stackrel{d}{=} \mathbf{A} \mathbf{W} \mathbf{A}^T$, $\mathbf{W} \sim W_p(m)$, $\Sigma = \mathbf{A} \mathbf{A}^T$. So for $p = 1$,

$$f_V(V) = \frac{1}{2^{m/2} \Gamma(\frac{m}{2}) \Sigma^{m/2}} V^{(m-2)/2} \text{etr} \left(-\frac{1}{2} \frac{V}{\Sigma} \right) \quad (23)$$

Note that $\Sigma = A^2$. Also for $p = 1$, $W \sim \chi_m^2$, so that

$$f_W(w) = \frac{1}{2^{m/2} \Gamma(\frac{m}{2})} w^{(m-2)/2} \exp \left(-\frac{1}{2} w \right), w > 0. \quad (24)$$

Now consider the Jacobian transformation $y = a^2 w = awa$, then $\frac{y}{a^2} = w$.

Then the Jacobian transformation J is $J(y \rightarrow w) = \frac{1}{a^2}$. Hence,

$$f_W(w) = \frac{1}{2^{m/2} \Gamma\left(\frac{m}{2}\right)} \left(\frac{y}{a^2}\right)^{(m-2)/2} \exp\left(-\frac{y}{a^2}\right) \left|\frac{1}{a^2}\right| \quad (25)$$

$$= \frac{1}{2^{m/2} \Gamma\left(\frac{m}{2}\right)} \frac{y^{(m-2)/2}}{(a^2)^{(m-2)/2}} \exp\left(-\frac{y}{a^2}\right) \left(\frac{1}{a^2}\right) \quad (26)$$

$$= \frac{1}{2^{m/2} \Gamma\left(\frac{m}{2}\right)} \frac{y^{(m-2)/2}}{(a^2)^{(m-2)/2}} \exp\left(-\frac{y}{a^2}\right) \quad (27)$$

$$= \frac{1}{2^{m/2} \Gamma\left(\frac{m}{2}\right)} \frac{y^{(m-2)/2}}{(a^2)^{(m-2)/2}} \text{etr}\left(-\frac{y}{a^2}\right). \quad (28)$$

Hence Equations (23) and (28) are equivalent if we let $V = y$ and $\Sigma = a^2$. Therefore Equation (22) is true for $p = 1$. Now let $r = 1$ and $s = p - 1$ in Proposition 7.9, then

$$\begin{aligned} V_{11.2} &\sim W(m - p + 1, \Sigma_{11.2}) \\ \mathbf{V}_{21} | \mathbf{V}_{22} &\sim \mathcal{N}_{p-1}(\mathbf{V}_{22} \Sigma_{22}^{-1} \Sigma_{21}, \mathbf{V}_{22} \Sigma_{11.2}) \\ \mathbf{V}_{22} &\sim W_{p-1}(m, \Sigma_{22}) \end{aligned}$$

where $V_{11.2} \perp (\mathbf{V}_{21}, \mathbf{V}_{22})$. Thus the joint density is given by,

$$\begin{aligned} &\frac{V_{11.2}^{(m-p+1)/2-1} \text{etr}\left(-\frac{1}{2} \frac{V_{11.2}}{\Sigma_{11.2}}\right)}{2^{(m-p+1)/2} \Gamma\left(\frac{m-p+1}{2}\right) \Sigma_{11.2}^{(m-p+1)/2}} \\ &\times \frac{\exp\left\{-\frac{1}{2} (\mathbf{V}_{21} - \mathbf{V}_{22} \Sigma_{22}^{-1} \Sigma_{21})^T (\Sigma_{11.2} \mathbf{V}_{22})^{-1} (\mathbf{V}_{21} - \mathbf{V}_{22} \Sigma_{22}^{-1} \Sigma_{21})\right\}}{(2\pi)^{(p-1)/2} |\Sigma_{11.2} \mathbf{V}_{22}|^{1/2}} \\ &\times \frac{|\mathbf{V}_{22}|^{(m-(p-1)-1)/2} \text{etr}\left(-\frac{1}{2} \Sigma_{22}^{-1} \mathbf{V}_{22}\right)}{2^{(m(p-1))/2} \Gamma_{p-1}\left(\frac{m}{2}\right) |\Sigma_{22}|^{m/2}} \quad (29) \end{aligned}$$

We make change of variables $(V_{11.2}, \mathbf{V}_{21}, \mathbf{V}_{22}) \rightarrow (V_{11}, \mathbf{V}_{21}, \mathbf{V}_{22})$, and since $V_{11.2} = V_{11} - \mathbf{V}_{12} \mathbf{V}_{22}^{-1} \mathbf{V}_{21}$. Then, $J[(V_{11.2}, \mathbf{V}_{21}, \mathbf{V}_{22}) \rightarrow (V_{11}, \mathbf{V}_{21}, \mathbf{V}_{22})] = |1|_+$. So that combining the factors in Equation (29) should lead to the Wishart density in Equation (22). In particular, the following enumeration attempts to summarize the process of simplifying Equation (29):

(a) Exponents of $\frac{1}{2}$:

$$\frac{(m - p + 1) + p - 1 + m(p - 1)}{2} = \frac{mp}{2}$$

(b) Combining the $\Gamma\left(\frac{m-p+1}{2}\right)$, $\Gamma_{p-1}\left(\frac{m}{2}\right)$, and $\pi^{(p-1)/2}$: Note that

$$\Gamma_{p-1}\left(\frac{m}{2}\right) = \pi^{(p-1)(p-2)/4} \prod_{i=1}^{p-1} \Gamma_{p-1}\left[\frac{m}{2} - \frac{1}{2}(i-1)\right] \quad (30)$$

So that if $i = p$, then

$$\Gamma_{p-1}\left[\frac{m}{2} - \frac{1}{2}(p-1)\right] = \Gamma_{p-1}\left(\frac{m-p+1}{2}\right). \quad (31)$$

Thus,

$$\begin{aligned} &\pi^{(p-1)/2} \pi^{(p-1)(p-2)/4} \Gamma_{p-1}\left(\frac{m-p+1}{2}\right) \prod_{i=1}^{p-1} \Gamma_{p-1}\left[\frac{m}{2} - \frac{1}{2}(i-1)\right] \\ &= \pi^{2(p-1)/4} \pi^{(p-1)(p-2)/4} \prod_{i=1}^p \Gamma_{p-1}\left[\frac{m}{2} - \frac{1}{2}(i-1)\right] \\ &= \pi^{p(p-1)/4} \prod_{i=1}^p \Gamma_{p-1}\left[\frac{m}{2} - \frac{1}{2}(i-1)\right] \\ &= \Gamma_{p-1}\left(\frac{m}{2}\right). \end{aligned}$$

(c) Combining $V_{11.2}^{(m-p+1)/2-1}$, $|\mathbf{V}_{22}|^{1/2}$, $|\mathbf{V}_{22}^{(m-p)/2}$:

$$\begin{aligned} V_{11.2}^{(m-p+1)/2-1} |\mathbf{V}_{22}|^{-1/2} |\mathbf{V}_{22}|^{(m-p)/2} &= V_{11.2}^{(m-p+1)/2-1} |\mathbf{V}_{22}|^{(m-p-1)/2} \\ &= |\mathbf{V}_{22}|^{(m-p-1)/2} \end{aligned}$$

(d) Combining $\Sigma_{11.2}^{(m-p+1)/2}$, $\Sigma_{11.2}^{-1/2}$, $|\Sigma_{22}|^{m/2}$:

$$\begin{aligned} \Sigma_{11.2}^{(m-p+1)/2} \Sigma_{11.2}^{-1/2} |\Sigma_{22}|^{m/2} &= \Sigma_{11.2}^{(m-p)/2} |\Sigma_{22}|^{m/2} \\ &= \Sigma_{11.2}^{m/2} \Sigma_{11.2}^{-p/2} |\Sigma_{22}|^{m/2} \\ &= \Sigma_{11.2}^{-p/2} (\Sigma_{11.2} |\Sigma_{22}|)^{m/2} \\ &= \Sigma_{11.2}^{-p/2} |\Sigma_{22}|^{m/2}. \end{aligned}$$

(e) Combining the exponential functions:

$$\begin{aligned} &\text{etr}\left(-\frac{1}{2} \frac{V_{11.2}}{\Sigma_{11.2}}\right) \text{etr}\left(-\frac{1}{2} \Sigma_{22}^{-1} \mathbf{V}_{22}\right) \\ &\times \exp\left\{-\frac{1}{2} (\mathbf{V}_{21} - \mathbf{V}_{22} \Sigma_{22}^{-1} \Sigma_{21})^T (\Sigma_{11.2} \mathbf{V}_{22})^{-1} (\mathbf{V}_{21} - \mathbf{V}_{22} \Sigma_{22}^{-1} \Sigma_{21})\right\}. \end{aligned}$$

Simplifying this and combining with the previous items should generate the Wishart distribution.

