

Homework 3

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1. $X_{p \times n} \sim N_{p \times n}(\mu 1_n^\top, \Delta \otimes \Sigma)$ is a normal random matrix. Let $Y = H_p X H_n$, where $H_p = I_p - 1_p 1_p^\top / p$ and $H_n = I_n - 1_n 1_n^\top / n$. Show that

1. $\sum_{j=1}^n Y_{ij} = \sum_{i=1}^p Y_{ij} = 0$ for all i and j .

2. $Y \sim N_{p \times n}(0, \Delta^Y \otimes \Sigma^Y)$, where

$$\begin{aligned} \sigma_{i,i'}^Y &= \sigma_{i,i'} - \sigma_{i.} - \sigma_{.i'} + \sigma_{..}, i, i' = 1, 2, \dots, p \\ \Delta_{j,j'}^Y &= \Delta_{j,j'} - \Delta_{.j} - \Delta_{j.} + \Delta_{..}, j, j' = 1, 2, \dots, n. \end{aligned}$$

Here dot “.” indicates an average over the missing index.

3. $\sum_{i'} \sigma_{i,i'}^Y = \sum_{j'} \Delta_{j,j'}^Y = 0$ for all i and j .

Solution. (a) Note that H_p and H_n are two projection matrices orthogonal to 1_p and 1_n , respectively. Therefore, we have $H_p 1_p = 0$ and $H_n 1_n = 0$. We use $e_k = (0, \dots, 1, \dots, 0)^\top$ to denote the vector with only the k -th entry being 1, and the dimension of e_k will be determined later according to matrix multiplication.

Since $\sum_{j=1}^n Y_{ij}$ is the sum of the i -th row of the matrix Y , we have

$$\sum_{j=1}^n Y_{ij} = e_i^\top Y 1_n = e_i^\top H_p X H_n 1_n = 0.$$

Similarly, since $\sum_{i=1}^p Y_{ij}$ is the sum of the j -th column of the matrix Y , we have

$$\sum_{i=1}^p Y_{ij} = 1_p^\top Y e_j = 1_p^\top H_p X H_n = 0.$$

(b) First,

$$Y = H_p X H_n \sim N_{p \times n}(H_p \mu 1_n^\top H_n, (H_n \Delta H_n) \otimes (H_p \Sigma H_p)) = N_{p \times n}(0, (H_n \Delta H_n) \otimes (H_p \Sigma H_p)),$$

and $\Delta^Y = H_n \Delta H_n, \Sigma^Y = H_p \Sigma H_p$. We further notice that

$$H_p e_i = e_i - \frac{1}{p} 1_p 1_p^\top e_i = e_i - \frac{1}{p} e_i.$$

Therefore, the (i, i') entry of Σ^Y is

$$\begin{aligned}\sigma_{i,i'}^Y &= e_i^\top \Delta^Y e_{i'} = e_i^\top H_p \Sigma H_p e_{i'} = (e_i - p^{-1} \mathbf{1}_p)^\top \Sigma (e_{i'} - p^{-1} \mathbf{1}_p) \\ &= e_i \Sigma e_{i'} - p^{-1} e_i^\top \Sigma \mathbf{1}_p - p^{-1} \Sigma e_{i'} + p^{-2} \mathbf{1}_p^\top \Sigma \mathbf{1}_p \\ &= \sigma_{i,i'} - \sigma_{i.} - \sigma_{.i'} + \sigma_{..}\end{aligned}$$

The result for Δ^Y follows the same argument, except for the difference between p and n and between σ and Δ .

(c) We have

$$\sum_{i'} \sigma_{i,i'}^Y = \sum_{i'} \sigma_{i,i'} - \sigma_{i.} - \sigma_{.i'} + \sigma_{..} = p\sigma_{i.} - p\sigma_{i.} - p\sigma_{..} + p\sigma_{..} = 0,$$

and the same result for Δ^Y . \square

2. Consider $X \sim N_{p \times n}(0, \Delta \otimes \Sigma)$, where $\Delta_{ii} = 1$ for all i . $\hat{\Sigma} = XX^T/n$. Show that $E(\hat{\Sigma}) = \Sigma$. Now consider $Y_{p \times n} \sim N_{p \times n}(0, I_n \otimes \Sigma)$. Let $\hat{\Sigma}_0 = YY^T/n$. Show that for all i, j, k, l , we have $Cov(\hat{\Sigma}_{ij}, \hat{\Sigma}_{kl}) = Cov((\hat{\Sigma}_0)_{ij}, (\hat{\Sigma}_0)_{kl})(1 + 2/n \sum_{g < h} \Delta_{gh}^2)$.

Solution.

$$E(\hat{\Sigma}) = E(XX^T/n) = 1/n \sum_{i=1}^n E(X_i X_i^T) = 1/n \sum_{i=1}^n Cov(X_i) = 1/n \sum_{i=1}^n \Delta_{ii} \Sigma = \Sigma.$$

$$\begin{aligned}Cov(\hat{\Sigma}_{ij}, \hat{\Sigma}_{kl}) &= 1/n^2 Cov\left(\sum_{r=1}^n X_{ir} X_{jr}, \sum_{s=1}^n X_{ks} X_{ls}\right) \\ &= 1/n^2 \left(\sum_{r=1}^n Cov(X_{ir} X_{jr}, X_{kr} X_{lr}) + 2 \sum_{r < s} Cov(X_{ir} X_{jr}, X_{ks} X_{ls}) \right).\end{aligned}$$

Notice that X_{ir} 's are normally distributed with mean 0, and by the formula of normal kurtosis :

$$\begin{aligned}&E((X_1 - E(X_1))(X_2 - E(X_2))(X_3 - E(X_3))(X_4 - E(X_4))) \\ &= Cov(X_1, X_2)Cov(X_3, X_4) + Cov(X_1, X_4)Cov(X_2, X_3) + Cov(X_1, X_3)Cov(X_2, X_4)\end{aligned}$$

We have:

$$\begin{aligned}Cov(X_{ir} X_{jr}, X_{ks} X_{ls}) &= E(X_{ir} X_{jr} X_{ks} X_{ls}) - E(X_{ir} X_{jr}) E(X_{ks} X_{ls}) \\ &= E(X_{ir} X_{ks}) E(X_{ls} X_{jr}) + E(X_{ir} X_{ls}) E(X_{is} X_{kr}) \\ &= \Delta_{rs}^2 \sigma_{ik} \sigma_{lj} + \Delta_{rs}^2 \sigma_{il} \sigma_{kj} \\ &= \Delta_{rs}^2 (\sigma_{ik} \sigma_{lj} + \sigma_{il} \sigma_{kj}) \\ Cov(\hat{\Sigma}_{ij}, \hat{\Sigma}_{kl}) &= 1/n^2 \left(\sum_{r=1}^n \Delta_{rr}^2 (\sigma_{ik} \sigma_{lj} + \sigma_{il} \sigma_{kj}) + 2 \sum_{r < s} \Delta_{rs}^2 (\sigma_{ik} \sigma_{lj} + \sigma_{il} \sigma_{kj}) \right) \\ &= (\sigma_{ik} \sigma_{lj} + \sigma_{il} \sigma_{kj}) / n (1 + 2/n \sum_{r < s} \Delta_{rs}^2)\end{aligned}$$

Specifically,

$$\begin{aligned} Cov((\hat{\Sigma}_0)_{ij}, (\hat{\Sigma}_0)_{kl}) &= 1/n^2 \left(\sum_{r=1}^n 1 \cdot (\sigma_{ik}\sigma_{lj} + \sigma_{il}\sigma_{kj}) + 2 \sum_{r<s} 0 \cdot (\sigma_{ik}\sigma_{lj} + \sigma_{il}\sigma_{kj}) \right) \\ &= (\sigma_{ik}\sigma_{lj} + \sigma_{il}\sigma_{kj})/n. \end{aligned}$$

So we have:

$$Cov(\hat{\Sigma}_{ij}, \hat{\Sigma}_{kl}) = Cov((\hat{\Sigma}_0)_{ij}, (\hat{\Sigma}_0)_{kl})(1 + 2/n \sum_{g<h} \Delta_{gh}^2)$$

3. Consider the mapping of $T \rightarrow S = T^T T$, which takes an upper triangular $p \times p$ matrix T into the symmetric matrix S . We mentioned in the class that $J(T \rightarrow S) = (2^p \prod_{i=1}^p t_{ii}^{p-i+1})^{-1}$. Now prove this result.

Solution. From

$$S = T^T T = \begin{pmatrix} t_{11} & 0 & \cdots & 0 \\ t_{12} & t_{22} & \cdots & 0 \\ \vdots & & & \\ t_{1p} & t_{2p} & \cdots & t_{pp} \end{pmatrix} \begin{pmatrix} t_{11} & t_{12} & \cdots & t_{1p} \\ 0 & t_{22} & \cdots & t_{2p} \\ \vdots & & & \\ 0 & 0 & \cdots & t_{pp} \end{pmatrix},$$

we have

$$\begin{pmatrix} s_{11} \\ s_{12} \\ \vdots \\ s_{1p} \\ \hline s_{22} \\ s_{23} \\ \vdots \\ s_{2p} \\ \hline \vdots \\ \hline s_{(p-1)(p-1)} \\ s_{(p-1)p} \\ \hline s_{pp} \end{pmatrix} = \begin{pmatrix} t_{11}^2 \\ t_{11}t_{12} \\ \vdots \\ t_{11}t_{1p} \\ \hline t_{12}^2 + t_{22}^2 \\ t_{12}t_{13} + t_{22}t_{23} \\ \vdots \\ t_{12}t_{1p} + t_{22}t_{2p} \\ \hline \vdots \\ \hline t_{1(p-1)}^2 + t_{2(p-1)}^2 + \cdots + t_{(p-1)(p-1)}^2 \\ t_{1(p-1)}t_{1p} + t_{2(p-1)}t_{2p} + \cdots + t_{(p-1)(p-1)}t_{(p-1)p} \\ \hline t_{1p}^2 + t_{2p}^2 + \cdots + t_{pp}^2 \end{pmatrix}.$$

5. Let $S \sim W_p(\Sigma, n)$. Calculate the expectation $E(\det(S^m))$, where m is a positive integer.

Solution. According to Bartlett's decomposition of the Wishart matrix S , we have

$$\det(S) = \det(\Sigma^{1/2} T^\top T \Sigma^{1/2}) = \det(\Sigma) \{\det(T)\}^2 = \det(\Sigma) \prod_{i=1}^p t_{ii}^2.$$

Therefore, we have

$$\begin{aligned} E(\det(S^m)) &= [\det(\Sigma)]^m E \left\{ \prod_{i=1}^p t_{ii}^{2m} \right\} = [\det(\Sigma)]^m \prod_{i=1}^p E(t_{ii}^{2m}) \\ &= [\det(\Sigma)]^m \prod_{i=1}^p E(\chi_{n-i+1}^2)^m = [\det(\Sigma)]^m \prod_{i=1}^p E \{2\text{Gamma}((n-i+1)/2)\}^m \\ &= [\det(\Sigma)]^m 2^{mp} \frac{\prod_{i=1}^p \Gamma\left(\frac{n-i+1}{2} + m\right)}{\prod_{i=1}^p \Gamma\left(\frac{n-i+1}{2}\right)}. \square \end{aligned}$$

6. (Expectation of the inverted Wishart distribution) If $S \sim W_p(\Sigma, n)$ with $n \geq p + 2$. Show that $E(S^{-1}) = \Sigma^{-1}/(n-p-1)$. Therefore, $(n-p-1)S^{-1}$ is an unbiased estimate of Σ^{-1} . Hint: Use the fact that for any constant vector a , $a^\top \Sigma^{-1} a / a^\top S^{-1} a \sim \chi_{n-p+1}^2$.

Solution. First, we notice that the expectation of a inverse chi-squared distribution with degrees of freedom ν is

$$E(1/\chi_\nu^2) = E\{2\text{Gamma}(\nu/2)\}^{-1} = \frac{\Gamma(\nu/2 - 1)}{\Gamma(\nu/2)} / 2 = \frac{1}{\nu - 2}.$$

If we take $a = (1, 0, \dots, 0)$, from $a^\top \Sigma^{-1} a / a^\top S^{-1} a = (\Sigma^{-1})_{11} / (S^{-1})_{11} \sim \chi_{n-p+1}^2$, we know

$$E(S^{-1})_{11} = (\Sigma^{-1})_{11} \times E(\chi_{n-p+1}^2)^{-1} = (\Sigma^{-1})_{11} / (n-p-1).$$

Similarly, we also have $E(S^{-1})_{22} = (\Sigma^{-1})_{22} / (n-p-1)$, and the same results hold for other diagonal terms.

If we take $a = (1, 1, 0, \dots, 0)$, from

$$a^\top \Sigma^{-1} a / a^\top S^{-1} a = \frac{(\Sigma^{-1})_{11} + \Sigma_{22}^{-1} + 2(\Sigma^{-1})_{12}}{(S^{-1})_{11} + (S^{-1})_{22} + 2(S^{-1})_{12}} \sim \chi_{n-p+1}^2,$$

we know

$$\begin{aligned} E[(S^{-1})_{11} + (S^{-1})_{22} + 2(S^{-1})_{12}] &= [(\Sigma^{-1})_{11} + \Sigma_{22}^{-1} + 2(\Sigma^{-1})_{12}] \times E(\chi_{n-p+1}^2)^{-1} \\ &= [(\Sigma^{-1})_{11} + \Sigma_{22}^{-1} + 2(\Sigma^{-1})_{12}] / (n-p-1). \end{aligned}$$

Since we have proved the diagonal terms, we have

$$E(S^{-1})_{12} = (\Sigma^{-1})_{12} / (n-p-1).$$

Proofs for other off-diagonal terms are similar. \square

Remark: you can also use the hint in this way,

$$E \left[\frac{a^T S^{-1} a}{a^T \Sigma^{-1} a} \right] = E(1/\chi^{n-p+1}) = \frac{1}{n-p-1}.$$

Therefore, for any a , we have

$$a^T \left(E [S^{-1}] - \frac{1}{n-p-1} \Sigma^{-1} \right) a = 0,$$

which implies the symmetric matrix $E [S^{-1}] - \frac{1}{n-p-1} \Sigma^{-1}$ is zero, i.e.

$$E [S^{-1}] = \frac{1}{n-p-1} \Sigma^{-1}.$$

(In the last step, consider the eigenvalue decomposition of the symmetric matrix.)