

# Assignment

Aryan Jain - EE22BTECH11011\*

**Question:** Suppose that  $\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_n, \mathbf{Y}_1, \mathbf{Y}_2, \dots, \mathbf{Y}_n$  are independent and identically distributed random vectors each having  $N_p(\boldsymbol{\mu}, \Sigma)$  distributions, where  $\Sigma$  is non-singular,  $p > 1$  and  $n > 1$ . If  $\mathbf{X} = \frac{1}{n} \sum_{i=1}^n \mathbf{X}_i$  and  $\mathbf{Y} = \frac{1}{n} \sum_{i=1}^n \mathbf{Y}_i$ , then which one of the following statements is true?

- (a) There exists  $c > 0$  such that  $c(\mathbf{X} - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{X} - \boldsymbol{\mu})$  has  $\chi^2$ -distribution with  $p$  degrees of freedom.
- (b) There exists  $c > 0$  such that  $c(\mathbf{X} - \mathbf{Y})^T \Sigma^{-1} (\mathbf{X} - \mathbf{Y})$  has  $\chi^2$ -distribution with  $(p - 1)$  degrees of freedom.
- (c) There exists  $c > 0$  such that  $c \sum_{i=1}^n (\mathbf{X}_i - \mathbf{X})^T \Sigma^{-1} (\mathbf{X}_i - \mathbf{X})$  has  $\chi^2$ -distribution with  $p$  degrees of freedom.
- (d) There exists  $c > 0$  such that  $c \sum_{i=1}^n (\mathbf{X}_i - \mathbf{Y}_i - \mathbf{X} + \mathbf{Y})^T \Sigma^{-1} (\mathbf{X}_i - \mathbf{Y}_i - \mathbf{X} + \mathbf{Y})$  has  $\chi^2$ -distribution with  $p$  degrees of freedom.

GATE ST Paper 2023

**Solution:**

We are given that,

$$\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_n, \mathbf{Y}_1, \mathbf{Y}_2, \dots, \mathbf{Y}_n \sim N_p(\boldsymbol{\mu}, \Sigma) \quad (1)$$

Also,

$$\mathbf{X} = \frac{1}{n} \sum_{i=1}^n \mathbf{X}_i \quad (2)$$

$$\mathbf{Y} = \frac{1}{n} \sum_{i=1}^n \mathbf{Y}_i \quad (3)$$

The mean of  $\mathbf{X}$  is given by:

$$\boldsymbol{\mu}_X = E(\mathbf{X}) \quad (4)$$

$$= \frac{1}{n} \sum_{i=1}^n E(\mathbf{X}_i) \quad (5)$$

$$= \boldsymbol{\mu} \quad (6)$$

Similarly,

$$\boldsymbol{\mu}_Y = \boldsymbol{\mu} \quad (7)$$

The covariance of  $\mathbf{X}$  is given by:

$$\Sigma_{\mathbf{X}} = E \left[ (\mathbf{X} - \boldsymbol{\mu}) (\mathbf{X} - \boldsymbol{\mu})^T \right] \quad (8)$$

$$= E \left[ \left( \frac{1}{n} \sum_{i=1}^n \mathbf{X}_i - \boldsymbol{\mu} \right) \left( \frac{1}{n} \sum_{i=1}^n \mathbf{X}_i - \boldsymbol{\mu} \right)^T \right] \quad (9)$$

$$= \frac{1}{n^2} E \left[ \sum_{i=1}^n (\mathbf{X}_i - \boldsymbol{\mu}) (\mathbf{X}_i - \boldsymbol{\mu})^T \right] \quad (10)$$

$$= \frac{1}{n^2} \left[ \sum_{i=1}^n E (\mathbf{X}_i^2 + \boldsymbol{\mu}^2 - 2\boldsymbol{\mu}\mathbf{X}_i) \right] \quad (11)$$

$$= \frac{1}{n^2} \left[ \sum_{i=1}^n E (\mathbf{X}_i^2) + \sum_{i=1}^n E (\boldsymbol{\mu}^2) - 2\boldsymbol{\mu} \sum_{i=1}^n E (\mathbf{X}_i) \right] \quad (12)$$

$$= \frac{1}{n^2} \left[ n\Sigma + n\boldsymbol{\mu}^2 + n\boldsymbol{\mu}^2 - 2\boldsymbol{\mu}^2 \right] \quad \left[ \because E (\mathbf{X}_i^2) = \Sigma_{\mathbf{X}_i} + E (\mathbf{X}_i)^2 \right] \quad (13)$$

$$= \frac{\Sigma}{n} \quad (14)$$

Similarly,

$$\Sigma_{\mathbf{Y}} = \frac{\Sigma}{n} \quad (15)$$

(a) To check option (A):

let us say,

$$\mathbf{A} = c(\mathbf{X} - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{X} - \boldsymbol{\mu}) \quad (16)$$

$$(17)$$

And,

$$\Sigma^{-1} = \mathbf{F}^T \mathbf{F} \quad (18)$$

$$\mathbf{y} = \mathbf{F} (\mathbf{X} - \boldsymbol{\mu}) \quad (19)$$

$$\implies \mathbf{A} = c\mathbf{y}^T \bar{\mathbf{y}} \quad (20)$$

$$= c\|\mathbf{y}\|^2 \quad (21)$$

Equation (21) shows that  $\mathbf{A}$  can have  $\chi^2$ -distribution.

To confirm that we will find the mean and covariance-matrix of  $\bar{\mathbf{y}}$ .

$$\boldsymbol{\mu}_{\mathbf{y}} = E (\mathbf{y}) \quad (22)$$

$$= E (\mathbf{F} (\mathbf{X} - \boldsymbol{\mu})) \quad (23)$$

$$= \mathbf{F} [E (\mathbf{X}) - E (\boldsymbol{\mu})] \quad (24)$$

$$= \mathbf{F} [\boldsymbol{\mu} - \boldsymbol{\mu}] \quad \text{from (6)} \quad (25)$$

$$= 0 \quad (26)$$

And,

$$\Sigma_{\mathbf{y}} = E \left[ (\mathbf{y} - \boldsymbol{\mu}_{\mathbf{y}}) (\mathbf{y} - \boldsymbol{\mu}_{\mathbf{y}})^T \right] \quad (27)$$

$$= E \left[ (\mathbf{F} (\mathbf{X} - \boldsymbol{\mu})) (\mathbf{F} (\mathbf{X} - \boldsymbol{\mu}))^T \right] \quad (28)$$

$$= E \left[ \mathbf{F} (\mathbf{X} - \boldsymbol{\mu}) (\mathbf{X} - \boldsymbol{\mu})^T \mathbf{F}^T \right] \quad (29)$$

$$= \mathbf{F} \left[ E \left[ (\mathbf{X} - \boldsymbol{\mu}) (\mathbf{X} - \boldsymbol{\mu})^T \right] \right] \mathbf{F}^T \quad (30)$$

$$= \mathbf{F} \Sigma \mathbf{F}^T \quad (31)$$

since,

$$\Sigma^{-1} = \mathbf{F}^T \mathbf{F} \quad (32)$$

$$\Sigma \Sigma^{-1} = \Sigma \mathbf{F}^T \mathbf{F} \quad (33)$$

$$\mathbf{I} = \Sigma \mathbf{F}^T \mathbf{F} \quad (34)$$

$$\mathbf{I} \mathbf{F}^{-1} = \Sigma \mathbf{F}^T \quad (35)$$

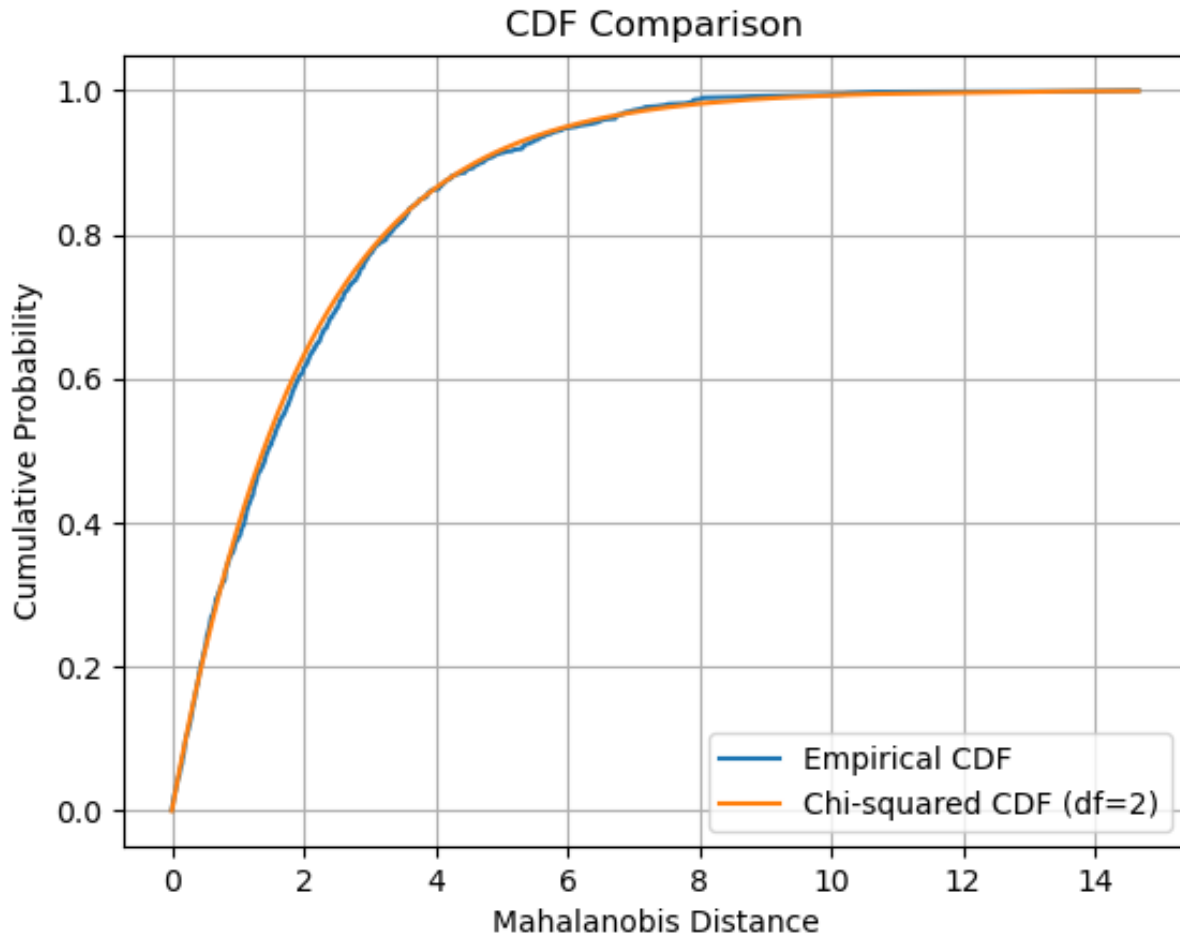
$$\mathbf{F} \mathbf{F}^{-1} = \mathbf{F} \Sigma \mathbf{F}^T \quad (36)$$

$$\mathbf{I} = \mathbf{F} \Sigma \mathbf{F}^T \quad (37)$$

So using (37),

$$\Sigma_y = \mathbf{I} \quad (38)$$

Hence, For  $c = 1$   $\mathbf{A}$  has  $\chi^2$ -distribution with  $p$  degrees of freedom.  
So option (A) is correct.



(b) To check option (B):

Let us say,

$$\mathbf{B} = c(\mathbf{X} - \mathbf{Y})^T \Sigma^{-1} (\mathbf{X} - \mathbf{Y}) \quad (39)$$

And,

$$\Sigma^{-1} = \mathbf{F}^T \mathbf{F} \quad (40)$$

$$\mathbf{y} = \mathbf{F} (\mathbf{X} - \mathbf{Y}) \quad (41)$$

$$\implies \mathbf{B} = c \mathbf{y}^T \bar{\mathbf{y}} \quad (42)$$

$$= c \|\mathbf{y}\|^2 \quad (43)$$

Equation (43) shows that  $\mathbf{B}$  can have  $\chi^2$ -distribution.

To confirm that we will find the mean and covariance-matrix of  $\bar{\mathbf{y}}$ .

$$\mu_{\mathbf{y}} = E(\mathbf{y}) \quad (44)$$

$$= E[\mathbf{F}(\mathbf{X} - \mathbf{Y})] \quad (45)$$

$$= \mathbf{F}[E(\mathbf{X}) - E(\mathbf{Y})] \quad (46)$$

$$= \mathbf{F}[\mu - \mu] \quad (47)$$

$$= 0 \quad (48)$$

And,

$$\Sigma_{\mathbf{y}} = E[(\mathbf{y} - \mu_{\mathbf{y}})(\mathbf{y} - \mu_{\mathbf{y}})^T] \quad (49)$$

$$= E[(\mathbf{F}(\mathbf{X} - \mathbf{Y}))(\mathbf{F}(\mathbf{X} - \mathbf{Y}))^T] \quad (50)$$

$$= E[\mathbf{F}(\mathbf{X} - \mathbf{Y})(\mathbf{X} - \mathbf{Y})^T \mathbf{F}^T] \quad (51)$$

$$= \mathbf{F}[E[(\mathbf{X} - \mathbf{Y})(\mathbf{X} - \mathbf{Y})^T]] \mathbf{F}^T \quad (52)$$

$$= \mathbf{F}[E[\|\mathbf{X} - \mathbf{Y}\|^2]] \mathbf{F}^T \quad (53)$$

$$= \mathbf{F}[E(\mathbf{X}^2) + E(\mathbf{Y}^2) - E(2\mathbf{X}\mathbf{Y})] \mathbf{F}^T \quad (54)$$

$$= \mathbf{F}\left[\frac{\Sigma}{n} + \mu^2 + \frac{\Sigma}{n} + \mu^2 - 2\mu^2\right] \mathbf{F}^T \quad [\because E(\mathbf{X}^2) = \Sigma_{\mathbf{X}} + E(\mathbf{X})^2] \quad (55)$$

$$= \frac{2}{n} \mathbf{F} \Sigma \mathbf{F}^T \quad (56)$$

$$= \frac{2}{n} \mathbf{I} \quad (57)$$

Hence, for  $c = \frac{n}{2}$ ,  $\mathbf{B}$  has  $\chi^2$ -distribution with p degrees of freedom.

So option (B) is incorrect.

(c) To check option (C):

let us say,

$$\mathbf{C} = c \sum_{i=1}^n (\mathbf{X}_i - \mathbf{X})^T \Sigma^{-1} (\mathbf{X}_i - \mathbf{X}) \quad (58)$$

And,

$$\Sigma^{-1} = \mathbf{F}^T \mathbf{F} \quad (59)$$

$$\mathbf{y} = \mathbf{F} \left( \sum_{i=1}^n (\mathbf{X}_i - \mathbf{X}) \right) \quad (60)$$

$$\implies \mathbf{C} = c \mathbf{y}^T \bar{\mathbf{y}} \quad (61)$$

$$= c \|\mathbf{y}\|^2 \quad (62)$$

Equation (62) shows that  $\mathbf{C}$  can have  $\chi^2$ -distribution.

To confirm that we will find the mean and covariance-matrix of  $\bar{\mathbf{y}}$ .

$$\boldsymbol{\mu}_{\mathbf{y}} = E(\mathbf{y}) \quad (63)$$

$$= E \left[ \mathbf{F} \left( \sum_{i=1}^n (\mathbf{X}_i - \mathbf{X}) \right) \right] \quad (64)$$

$$= \mathbf{F} \left[ \sum_{i=1}^n (E(\mathbf{X}_i) - E(\mathbf{X})) \right] \quad (65)$$

$$= \mathbf{F} [E(X_1) - E(X) + E(X_2) - E(X) + \dots + E(X_n) - E(X)] \quad (66)$$

$$= 0 \quad (67)$$

And,

$$\Sigma_{\mathbf{y}} = E \left[ (\mathbf{y} - \boldsymbol{\mu}_{\mathbf{y}})(\mathbf{y} - \boldsymbol{\mu}_{\mathbf{y}})^T \right] \quad (68)$$

$$= \mathbf{F} E \left[ \left( \sum_{i=1}^n (\mathbf{X}_i - \mathbf{X}) \right) \left( \sum_{i=1}^n (\mathbf{X}_i - \mathbf{X}) \right)^T \right] \mathbf{F}^T \quad (69)$$

$$= \mathbf{F} E \left[ \left( \sum_{i=1}^n \mathbf{X}_i - n\mathbf{X} \right) \left( \sum_{i=1}^n \mathbf{X}_i - n\mathbf{X} \right)^T \right] \mathbf{F}^T \quad (70)$$

$$= \mathbf{F} E \left[ (n\mathbf{X} - n\mathbf{X})(n\mathbf{X} - n\mathbf{X})^T \right] \mathbf{F}^T \quad (71)$$

$$= \mathbf{F} \mathbf{0} \mathbf{F}^T \quad (72)$$

$$= \mathbf{0} \quad (73)$$

Hence, There is no value of  $c > 0$  for which  $\mathbf{C}$  have  $\chi^2$ -distribution.

So option (C) is incorrect.

(d) To check option (D):

let us say,

$$\mathbf{D} = c \sum_{i=1}^n (\mathbf{X}_i - \mathbf{Y}_i - \mathbf{X} + \mathbf{Y})^T \Sigma^{-1} (\mathbf{X}_i - \mathbf{Y}_i - \mathbf{X} + \mathbf{Y}) \quad (74)$$

And,

$$\Sigma^{-1} = \mathbf{F}^T \mathbf{F} \quad (75)$$

$$\mathbf{y} = \mathbf{F} \left( \sum_{i=1}^n (\mathbf{X}_i - \mathbf{Y}_i - \mathbf{X} + \mathbf{Y}) \right) \quad (76)$$

$$\Rightarrow \mathbf{C} = c \mathbf{y}^T \bar{\mathbf{y}} \quad (77)$$

$$= c \|\mathbf{y}\|^2 \quad (78)$$

Equation (78) shows that  $\mathbf{D}$  can have  $\chi^2$ -distribution.

To confirm that we will find the mean and covariance-matrix of  $\bar{\mathbf{y}}$ .

$$\boldsymbol{\mu}_{\mathbf{y}} = E(\mathbf{y}) \quad (79)$$

$$= E\left(\mathbf{F}\left(\sum_{i=1}^n (\mathbf{X}_i - \mathbf{Y}_i - \mathbf{X} + \mathbf{Y})\right)\right) \quad (80)$$

$$= \mathbf{F}E\left[\sum_{i=1}^n \mathbf{X}_i - \sum_{i=1}^n \mathbf{Y}_i - n\mathbf{X} + n\mathbf{Y}\right] \quad (81)$$

$$= \mathbf{F}\left[\sum_{i=1}^n E(\mathbf{X}_i) - \sum_{i=1}^n E(\mathbf{Y}_i) - nE(\mathbf{X}) + nE(\mathbf{Y})\right] \quad (82)$$

$$= \mathbf{F}[n\boldsymbol{\mu} - n\boldsymbol{\mu} - n\boldsymbol{\mu} + n\boldsymbol{\mu}] \quad (83)$$

$$= 0 \quad (84)$$

And,

$$\Sigma_{\mathbf{y}} = E\left[(\mathbf{y} - \boldsymbol{\mu}_{\mathbf{y}})(\mathbf{y} - \boldsymbol{\mu}_{\mathbf{y}})^T\right] \quad (85)$$

$$= \mathbf{F}E\left[\left(\sum_{i=1}^n (\mathbf{X}_i - \mathbf{Y}_i - \mathbf{X} + \mathbf{Y})\right)\left(\sum_{i=1}^n (\mathbf{X}_i - \mathbf{Y}_i - \mathbf{X} + \mathbf{Y})\right)^T\right]\mathbf{F}^T \quad (86)$$

$$= \mathbf{F}E\left[\left(\sum_{i=1}^n \mathbf{X}_i - \sum_{i=1}^n \mathbf{Y}_i - n\mathbf{X} + n\mathbf{Y}\right)\left(\sum_{i=1}^n \mathbf{X}_i - \sum_{i=1}^n \mathbf{Y}_i - n\mathbf{X} + n\mathbf{Y}\right)^T\right]\mathbf{F}^T \quad (87)$$

$$= \mathbf{F}E\left[(n\mathbf{X} - n\mathbf{Y} - n\mathbf{X} + n\mathbf{Y})(n\mathbf{X} - n\mathbf{Y} - n\mathbf{X} + n\mathbf{Y})^T\right]\mathbf{F}^T \quad (88)$$

$$= \mathbf{F}\mathbf{0}\mathbf{F}^T \quad (89)$$

$$= \mathbf{0} \quad (90)$$

Hence, There is no value of  $c > 0$  for which  $\mathbf{D}$  have  $\chi^2$ -distribution.

So option (D) is incorrect.

Steps for simulation:

- 1) Firstly in the the file "gauss.c", I have generated 1000 random vectors with dimension 2 using Box-Muller method and listed the data in the file "randomvectors.dat".
- 2) Then in the file "distance.c", using the random vectors generated in the first step, I found the value of  $c(\mathbf{X} - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{X} - \boldsymbol{\mu})$  distribution which will give us  $1 \times 1$  matrix.
- 3) So as we have generated 1000 random vectors in first step, we will have 1000 values of the distribution.
- 4) Then I have listed the values of the distribution  $c(\mathbf{X} - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{X} - \boldsymbol{\mu})$  that I got in the file "mahalanobisdistances.dat".
- 5) Now in the file "cdf.py", I have plotted the cdf of the distribution  $c(\mathbf{X} - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{X} - \boldsymbol{\mu})$  and also plotted the theoretical cdf plot of a  $\chi^2$  distribution.