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Assignment 8

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Download all python codes from

https://github.com/Adarsh541/AI1103-prob-andranvar/blob/main/Assignment8.1/codes/ Assignment8.1.py

and latex-tikz codes from

https://github.com/Adarsh541/AI1103-prob-andranvar/blob/main/Assignment8.1/Assignment8 .1.tex

1 Problem

Let X_1, X_2, X_3, X_4, X_5 be a random sample of size 5 from a population having standard normal distribution. If $\overline{X} = \frac{1}{5} \sum_{i=1}^{5} X_i$ and $T = \sum_{i=1}^{5} (X_i - \overline{X})^2$ then $E[T^2\overline{X}^2]$ is equal to

- 1) 3
- 2) 3.6
- 3) 4.8
- 4) 5.2

2 Solution

2.1 Terminology

Let $\mathbf{x} \sim N(\mathbf{0}, \mathbf{I})$ be a standard normal random vector

$$\mathbf{x} = \begin{pmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \end{pmatrix} \tag{2.1.1}$$

Then \overline{X} can be written as

$$\overline{X} = \frac{1}{5} \mathbf{u}^{\mathsf{T}} \mathbf{x} \tag{2.1.2}$$

where

$$\mathbf{1} = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \tag{2.1.3}$$

$$T = \mathbf{x}^{\mathsf{T}} \mathbf{M} \mathbf{x} \tag{2.1.4}$$

where

$$\mathbf{M} = \begin{pmatrix} \frac{4}{5} & -1/5 & -1/5 & -1/5 & -1/5 \\ -1/5 & \frac{4}{5} & -1/5 & -1/5 & -1/5 \\ -1/5 & -1/5 & \frac{4}{5} & -1/5 & -1/5 \\ -1/5 & -1/5 & -1/5 & \frac{4}{5} & -1/5 \\ -1/5 & -1/5 & -1/5 & -1/5 & \frac{4}{5} \end{pmatrix} (2.1.5)$$

$$(2.1.6)$$

we also have

$$\mathbf{M}^2 = \mathbf{M} \tag{2.1.7}$$

2.2 Theorem

Let $\overline{X_n}$ be the sample mean of size n from a normal distribution with mean μ and variance σ^2 . Then

- 1) $\overline{X_n} \sim N(\mu, \frac{\sigma^2}{n})$

2) \overline{X} and S^2 are independent. 3) $\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2$ where χ_{n-1}^2 is chi-square distribution with (n-1) degrees of freedom and S^2 is defined as

$$S^{2} = \frac{1}{n-1} \sum_{i=1}^{n} (X_{i} - \overline{X})^{2}$$
 (2.2.1)

2.3 Useful concepts

If X,Y are independent random variables.then

$$E[XY] = E[X]E[Y] \tag{2.3.1}$$

$$E[X^2] = Var[X] + (E[X])^2$$
 (2.3.2)

If X is chi-square distributed with parameter k,then

$$E[X] = k \tag{2.3.3}$$

$$Var\left[X\right] = 2k\tag{2.3.4}$$

2.4 solution

(2.1.3) For standard normal distribution $\mu = 0, \sigma^2 = 1.$ So from the above theorem for n = 5 we have

- 1) T/4 and \overline{X} are independent.
- 2) $\overline{X} \sim N(0, 1/5)$

3)
$$T \sim \chi_4^2$$

So from (2.3.3) and (2.3.4)

$$E[T] = 4$$
 (2.4.1)

$$Var[T] = 8 \tag{2.4.2}$$

Since $\frac{T}{4}$ and \overline{X} are independent,T and \overline{X} are also independent

$$E[T^2\overline{X}^2] = E[T^2]E[\overline{X}^2] \tag{2.4.3}$$

from (2.3.2)

$$E[\overline{X}^2] = \frac{1}{5} \tag{2.4.4}$$

$$E[T^2] = 24 (2.4.5)$$

So from (2.4.3)

$$E[T^2\overline{X}^2] = 4.8 \tag{2.4.6}$$

3 Proof for Independency

$$\overline{X} = \frac{1}{5} \mathbf{u}^{\mathsf{T}} \mathbf{x} \tag{3.0.1}$$

since M is symmetric and idempotent we have

$$T = \mathbf{x}^{\mathsf{T}} \mathbf{M} \mathbf{x} \tag{3.0.2}$$

$$= \mathbf{x}^{\mathsf{T}} \mathbf{M} \mathbf{M} \mathbf{x} \tag{3.0.3}$$

$$= \mathbf{x}^{\mathsf{T}} \mathbf{M}^{\mathsf{T}} \mathbf{M} \mathbf{x} \tag{3.0.4}$$

$$= (\mathbf{M}\mathbf{x})^{\mathsf{T}} (\mathbf{M}\mathbf{x}) \tag{3.0.5}$$

From (3.0.1) it can be seen that \overline{X} depends only on $\mathbf{u}^{\mathsf{T}}\mathbf{x}$ and from (3.0.5) it can be seen that T depends only on $\mathbf{M}\mathbf{x}$. So if $\mathbf{M}\mathbf{x}$ and $\mathbf{u}^{\mathsf{T}}\mathbf{x}$ are independent then T and \overline{X} are also independent

3.1 Identity

$$(\mathbf{u}^{\mathsf{T}}\mathbf{x})(\mathbf{x}^{\mathsf{T}}\mathbf{v}) = \mathbf{u}^{\mathsf{T}}(\mathbf{x}\mathbf{x}^{\mathsf{T}})\mathbf{v} \tag{3.1.1}$$

This identity is verified using python.

3.2 Cross-Covariance

$$Cov[\mathbf{x}, \mathbf{y}] = E[(\mathbf{x} - E[\mathbf{x}])(\mathbf{y} - E[\mathbf{y}])^{\mathsf{T}}]$$
 (3.2.1)

Two jointly normal vectors are independent if and only if their cross-covariance is zero.

$$Cov\left[\mathbf{u}^{\mathsf{T}}\mathbf{x}, \mathbf{M}\mathbf{x}\right] = E[(\mathbf{u}^{\mathsf{T}}\mathbf{x} - E[\mathbf{u}^{\mathsf{T}}\mathbf{x}])$$
$$(\mathbf{M}\mathbf{x} - E[\mathbf{M}\mathbf{x}])^{\mathsf{T}}] \quad (3.2.2)$$

using the identity stated in section 3.1 we get

$$Cov\left[\mathbf{u}^{\mathsf{T}}\mathbf{x}, \mathbf{M}\mathbf{x}\right] = \mathbf{u}^{\mathsf{T}}E[(\mathbf{x} - E[\mathbf{x}])(\mathbf{x} - E[\mathbf{x}])^{\mathsf{T}}]\mathbf{M}^{\mathsf{T}}$$
(3.2.3)

$$= \mathbf{u}^{\mathsf{T}} Var[\mathbf{x}] \mathbf{M} \tag{3.2.4}$$

$$= \mathbf{u}^{\mathsf{T}} \mathbf{M} \tag{3.2.5}$$

$$=0$$
 (3.2.6)

So $\mathbf{M}\mathbf{x}$ and $\mathbf{u}^{\mathsf{T}}\mathbf{x}$ are independent. This implies \overline{X} and T are independent.