

Assignment 8

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Download all python codes from

<https://github.com/Adarsh541/AI1103-prob-and-ranvar/blob/main/Assignment8.1/codes/Assignment8.1.py>

and latex-tikz codes from

<https://github.com/Adarsh541/AI1103-prob-and-ranvar/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 $\bar{X} = \frac{1}{5} \sum_{i=1}^5 X_i$ and $T = \sum_{i=1}^5 (X_i - \bar{X})^2$ then $E[T^2 \bar{X}^2]$ is equal to

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

2 SOLUTION

2.1 Theorem

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

- 1) $\bar{X}_n \sim N(\mu, \frac{\sigma^2}{n})$
- 2) \bar{X} and T are independent.
- 3) $\frac{T}{\sigma^2} \sim \chi_{n-1}^2$

where χ_{n-1}^2 is chi-square distribution with $(n-1)$ degrees of freedom and T is as defined in the question.

2.2 Useful concepts

If X, Y are independent random variables, then

$$E[XY] = E[X]E[Y] \quad (2.2.1)$$

$$E[X^2] = \text{Var}[X] + (E[X])^2 \quad (2.2.2)$$

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

$$E[X] = k \quad (2.2.3)$$

$$\text{Var}[X] = 2k \quad (2.2.4)$$

2.3 solution

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

1) T and \bar{X} are independent.

2) $\bar{X} \sim N(0, 1/5)$

3) $T \sim \chi_4^2$

So from (2.2.3) and (2.2.4)

$$E[T] = 4 \quad (2.3.1)$$

$$\text{Var}[T] = 8 \quad (2.3.2)$$

Since T and \bar{X} are independent

$$E[T^2 \bar{X}^2] = E[T^2]E[\bar{X}^2] \quad (2.3.3)$$

from (2.2.2)

$$E[\bar{X}^2] = \frac{1}{5} \quad (2.3.4)$$

$$E[T^2] = 24 \quad (2.3.5)$$

So from (2.3.3)

$$E[T^2 \bar{X}^2] = 4.8 \quad (2.3.6)$$

3 INDEPENDENCY

In this section we will prove that for a normally distributed population the sample mean and sample variance are independent. The sample mean is defined as

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i \quad (3.0.1)$$

the sample variance is defined as

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2 \quad (3.0.2)$$

where X_i are i.i.d and normally distributed and n is the sample size.

3.1 properties of mean and variance

If X and Y are independent random variables

$$E[aX + bY] = aE[X] + bE[Y] \quad (3.1.1)$$

$$Var[aX + b] = a^2 Var[X] \quad (3.1.2)$$

$$Var[aX + bY] = a^2 Var[X] + b^2 Var[Y] \quad (3.1.3)$$

3.2 properties of covariance

If X,Y,Z are random variables and a,b are constants

$$Cov[aX, bY] = ab \times Cov[X, Y] \quad (3.2.1)$$

$$Cov[X + Z, Y] = Cov[X, Y] + Cov[Z, Y] \quad (3.2.2)$$

$$Cov[X, X] = Var[X] \quad (3.2.3)$$

Since X_i are i.i.d

$$Cov[X_j, \bar{X}] = \frac{1}{n} Cov[X_j, X_j] \quad (3.4.6)$$

$$= \frac{\sigma^2}{n} \quad (3.4.7)$$

So from (3.4.3) and (3.4.7)

$$Cov[X_j - \bar{X}, \bar{X}] = \frac{\sigma^2}{n} - \frac{\sigma^2}{n} \quad (3.4.8)$$

$$= 0 \quad (3.4.9)$$

From (3.4.9) and property on multivariate normal distribution stated above, it follows that \bar{X} and $X = (X_1 - \bar{X}, \dots, X_n - \bar{X})^T$ are independent normal vectors, and so \bar{X} is independent of $X^T X = (n-1)S^2$

3.3 Multivariate normal distribution

One definition is that a random vector is said to be a k-variate normally distributed if every linear combination of its k components has univariate normal distribution. If a random vector has multivariate normal distribution then any two or more of its components that are uncorrelated are independent.

3.4 proof

X_i are i.i.d and normally distributed with mean μ and variance σ^2 . Consider

$$\begin{aligned} \bar{X} - X_j &= \frac{1}{n} (X_1 + \dots + X_{j-1} + X_{j+1} + \dots + X_n) \\ &\quad - \left(\frac{n-1}{n} \right) X_j \end{aligned} \quad (3.4.1)$$

from properties of mean and variance

$$\bar{X} - X_j = N\left(0, \frac{n-1}{n} \sigma^2\right) \quad (3.4.2)$$

This implies the vector $(\bar{X}, X_1 - \bar{X}, \dots, X_n - \bar{X})^T$ has multivariate normal distribution. Furthermore we have

$$Cov[X_j - \bar{X}, \bar{X}] = Cov[X_j, \bar{X}] - Cov[\bar{X}, \bar{X}] \quad (3.4.3)$$

1)

$$Cov[X_j, \bar{X}] = Cov\left[X_j, \frac{1}{n} \sum_{i=1}^n X_i\right] \quad (3.4.4)$$

$$= \frac{1}{n} \sum_{i=1}^n Cov[X_j, X_i] \quad (3.4.5)$$