

# Assignment 5

Course name: PROBABILITY AND STOCHASTIC PROCESSES (AI5030)

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KSHITIZ KUMAR | AI22MTECH02002 | ai22mtech02002@iith.ac.in

Question 1 . . . . . 1

## Question 1

Which of the following are correct?

1. If  $X$  and  $Y$  are independent  $\mathcal{N}(0, 1)$ , then  $\frac{X+Y}{\sqrt{2}}$  is  $\mathcal{N}(0, 1)$ .
2. If  $X$  and  $Y$  are independent  $\mathcal{N}(0, 1)$ , then  $\frac{X}{Y}$  has t-distribution.
3. If  $X$  and  $Y$  are independent  $\mathcal{U}ni form(0, 1)$ , then  $(\frac{X+Y}{2})$  is  $\mathcal{U}ni form(0, 1)$ .
4. If  $X$  is  $\mathcal{B}inomial(n, p)$ , then  $n - X$  is  $\mathcal{B}inomial(n, 1 - p)$ .

**Answer:**

**Theorem 1** (Uniqueness Theorem). *If two random variables have same moment generating functions, then they have the same distribution.*

**Theorem 2.** *Product of normally distributed random variables with a constant gives a normally distributed random variable.*

*i.e.,  $X \sim \mathcal{N}(\mu, \sigma^2)$  and,  $Z = kX$ , where  $k$  is a constant, then-*

$$Z \sim \mathcal{N}(k\mu, (k\sigma)^2)$$

**Proof:**

Moment Generating Function of a Normal Random Variable  $X \sim \mathcal{N}(\mu, \sigma^2)$  is given as-

$$M_X(t) = E[e^{tX}] = e^{\left(\mu_X t + \frac{\sigma_X^2 t^2}{2}\right)}$$

$$\begin{aligned}
\therefore M_Z(t) &= E[e^{tZ}] \\
&= \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{tz} e^{-\frac{1}{2}\left(\frac{(x-\mu)^2}{\sigma^2}\right)} dx \\
&= \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{ktx} e^{-\frac{1}{2}\left(\frac{(x-\mu)^2}{\sigma^2}\right)} dx \\
\text{Let, } y &= \frac{x-\mu}{\sigma} \\
\Rightarrow dy &= \frac{dx}{\sigma} \\
&= \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{kt(\mu+\sigma y)} e^{-\frac{1}{2}y^2} dy \\
&= \frac{e^{k\mu t}}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}((y-k\sigma t)^2 - (k\sigma t)^2)} dy \\
&= \left( \frac{e^{\left(k\mu t + \frac{(k\sigma)^2 t^2}{2}\right)}}{\sqrt{2\pi}} \right) \int_{-\infty}^{\infty} e^{-\frac{1}{2}(y-k\sigma t)^2} dy
\end{aligned}$$

Since, the integral has an Even function.

$$= \left( \frac{2e^{\left(k\mu t + \frac{(k\sigma)^2 t^2}{2}\right)}}{\sqrt{2\pi}} \right) \int_0^{\infty} e^{-\frac{1}{2}(y-k\sigma t)^2} dy \quad (1)$$

$$\begin{aligned}
\text{Let, } r &= \frac{1}{2}(y-k\sigma t)^2 \\
\Rightarrow dy &= \frac{dr}{\sqrt{2r}} \\
&= \left( \frac{2e^{\left(k\mu t + \frac{(k\sigma)^2 t^2}{2}\right)}}{\sqrt{2\pi}} \right) \int_0^{\infty} \frac{e^{-r}}{\sqrt{2r}} dr \\
&= \left( \frac{e^{\left(k\mu t + \frac{(k\sigma)^2 t^2}{2}\right)}}{\sqrt{\pi}} \right) \int_0^{\infty} r^{-\frac{1}{2}} e^{-r} dr
\end{aligned}$$

Evaluating the integral using the gamma function, we get-

$$\begin{aligned}
&= \left( \frac{e^{\left(k\mu t + \frac{(k\sigma)^2 t^2}{2}\right)}}{\sqrt{\pi}} \right) \times \Gamma\left(\frac{1}{2}\right) \\
&= \left( \frac{e^{\left(k\mu t + \frac{(k\sigma)^2 t^2}{2}\right)}}{\sqrt{\pi}} \right) \times (\sqrt{\pi}) \\
&= e^{\left((k\mu)t + \frac{(k\sigma)^2 t^2}{2}\right)}
\end{aligned}$$

**Theorem 3.** Sum of two independent normally distributed random variables is a normally distributed random variable.

$$X \sim \mathcal{N}(\mu_X, \sigma_X^2)$$

$$Y \sim \mathcal{N}(\mu_Y, \sigma_Y^2)$$

and,  $Z = X + Y$ , then-

$$Z \sim \mathcal{N}(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2)$$

**Proof:**

$$\begin{aligned} \therefore M_Z(t) &= E[e^{tZ}] \\ &= E[e^{t(X+Y)}] \\ &= E[e^{tX}]E[e^{tY}] \\ &= e^{\left(\mu_X t + \frac{\sigma_X^2 t^2}{2}\right)} \times e^{\left(\mu_Y t + \frac{\sigma_Y^2 t^2}{2}\right)} \\ &= e^{\left((\mu_X + \mu_Y)t + \frac{(\sigma_X^2 + \sigma_Y^2)t^2}{2}\right)} \end{aligned} \quad (2)$$

**Definition 4** (Ratio Distribution). A Ratio Distribution is a probability distribution constructed as the distribution of the ratio of random variables having two other known distributions.

Given two (usually independent) random variables  $X$  and  $Y$ , the distribution of the random variables  $X = \left(\frac{U}{V}\right)$  is a ratio distribution.

**Theorem 5.** Ratio distribution of two standard normally distributed variables is a standard cauchy distribution.

**Proof:** PDF of  $U$  and  $V$  is given as,

$$f_U(u) = \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{u^2}{2}}, f_V(v) = \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{v^2}{2}} \quad (3)$$

where  $-\infty < u, v < \infty$

Since  $U$  and  $V$  are independent, their joint PDF is given by,

$$f_{UV}(u, v) = \frac{1}{2\pi} \cdot e^{-\frac{u^2 + v^2}{2}} \quad (4)$$

$$F_X(x) = P(X \leq x) = P\left(\frac{U}{V} \leq x\right) \quad (5)$$

$$= P(U \leq V \cdot x, V \geq 0) + P(U \geq V \cdot x, V < 0) \quad (6)$$

$$= \int_0^\infty \int_{-\infty}^{v.x} f_{uv}(u, v) du dv + \int_{-\infty}^0 \int_{-\infty}^{v.x} f_{uv}(u, v) du dv \quad (7)$$

Differentiating  $F_X(x)$  to obtain PDF of  $X$ ,  $f_X(x)$   
(Using Leibniz's Integral Rule)

$$f_X(x) = \int_0^\infty v \cdot f_{uv}(vx, v) dv + \int_{-\infty}^0 (-v) \cdot f_{uv}(vx, v) dv \quad (8)$$

$$f_X(x) = \int_0^\infty v \cdot \frac{1}{2\pi} \cdot e^{-\frac{(1+x^2)v^2}{2}} dv + \int_{-\infty}^0 (-v) \cdot \frac{1}{2\pi} \cdot e^{-\frac{(1+x^2)v^2}{2}} dv \quad (9)$$

Let,

$$u = \frac{(1+x^2)v^2}{2} \quad (10)$$

$$\frac{du}{dv} = (1+x^2)v \Rightarrow dv = \frac{du}{(1+x^2)v} \quad (11)$$

$$f_X(x) = \int_0^\infty \frac{1}{2\pi(1+x^2)} \cdot e^{-u} du - \int_{-\infty}^0 \frac{1}{2\pi(1+x^2)} \cdot e^{-u} du \quad (12)$$

$$f_X(x) = \frac{1}{\pi(1+x^2)} \quad (13)$$

Hence,  $X \sim \text{Cauchy}(0,1)$

**Theorem 6.** Product of Uniform Random Variable with a constant results in a Uniform Random Variable.

i.e.,  $X \sim \mathcal{U}ni\text{form}(a,b)$  and  $Z = kX$ , where  $k$  is a constant, then-

$$Z \sim \mathcal{U}ni\text{form}(ka, kb)$$

**Proof:**

Moment Generating Function of Uniform Distribution  $X \sim \mathcal{U}ni\text{form}(a,b)$  is given as-

$$M_X(t) = E[e^{tX}] = \frac{e^{tb} - e^{ta}}{t(b-a)}$$

$$\begin{aligned} \therefore M_Z(t) &= E[e^{tZ}] \\ &= \int_{-\infty}^\infty e^{t(kx)} f_X(x) dx \\ &= \int_a^b e^{t(kx)} \left( \frac{1}{b-a} \right) dx \\ &= \left( \frac{1}{b-a} \right) \left[ \frac{e^{t(kx)}}{kt} \right]_a^b \\ &= \frac{e^{t(kb)} - e^{t(ka)}}{t((kb) - (ka))} \end{aligned} \quad (14)$$

**Theorem 7.** Sum of two independent, uniform random variables is not uniform.

$$X \sim \mathcal{U}(a, b)$$

$$Y \sim \mathcal{U}(a, b)$$

and,  $Z = X + Y$ , then  $Z$  is not Uniformly distributed.

**Proof:**

$$\begin{aligned} \therefore M_Z(t) &= E[e^{tZ}] \\ &= E[e^{t(X+Y)}] \\ &= E[e^{tX}]E[e^{tY}] \\ &= \left( \frac{e^{tb} - e^{ta}}{t(b-a)} \right) \times \left( \frac{e^{tb} - e^{ta}}{t(b-a)} \right) \\ &= \left( \frac{e^{tb} - e^{ta}}{t(b-a)} \right)^2 \end{aligned} \tag{15}$$

From theorem (1), we can conclude that- since, this moment generating function is not similar to that of uniform random variable's moment, this distribution is not uniform.

**Theorem 8.** Binomial Random Variable  $X$  counts the number of successes in ' $n$ ' independent Bernoulli trials.

i.e.,  $X = X_1 + X_2 + \dots + X_n$ ; where,  $X_i \sim \text{Bernoulli}(p) \sim \mathcal{B}(p)$

then,  $X \sim \text{Binomial}(n, p) \sim b(n, p)$ .

**Proof:**

Moment Generating Function of  $X_i \sim \mathcal{B}(p)$  is given as-

$$\begin{aligned} \therefore M_{X_i}(t) &= E[e^{tX_i}] \\ &= e^{t \times 0} \times q + e^{t \times 1} \times p \\ &= q + pe^t \end{aligned}$$

For summation of independent random variables, Moment generating function is written as-

$$\begin{aligned} \therefore M_X(t) &= \prod_{i=1}^n M_{X_i}(t) \\ &= \prod_{i=1}^n E[e^{tX_i}] \\ &= (q + pe^t)^n \end{aligned}$$

Using Binomial formula, we get-

$$(a + b)^n = \sum_{x=0}^n \binom{n}{k} a^x b^{n-x}$$

$$= \sum_{x=0}^n \binom{n}{k} (pe^t)^x (q)^{n-x}$$

**Theorem 9.** If  $X$  is Bernoulli random variable with success probability  $p$ , i.e.,  $X \sim \mathcal{B}(p)$ , then,  $Z = (1 - X) \sim \mathcal{B}(p)$ .

**Proof:**

$$\begin{aligned}\therefore M_Z(t) &= E[e^{tZ}] \\ &= \sum_{x=0,1} e^{t(1-x)} f_X(x) \\ &= e^{t \times (1-0)} \times q + e^{t \times (1-1)} \times p \\ &= qe^t + p\end{aligned}$$

Hence,  $Z \sim \mathcal{B}(q) \sim \mathcal{B}(1 - p)$ .

**Analysis of Option ① :**

From theorem ② and ③, we can say that option ① is correct.

**Analysis of Option ② :**

From theorem ⑤, we can conclude that option ② is incorrect.

**Analysis of Option ③ :**

From theorem ⑦, we can conclude that option ③ is incorrect.

**Analysis of Option ④ :**

From theorem ⑧, we know that-

if  $X_i \sim \mathcal{B}(p)$ , then  $X = \sum_{i=1}^{i=n} X_i \sim b(n, p)$ .

From theorem ⑨, we know that-

if  $X_i \sim \mathcal{B}(p)$ , then  $Z_i = (1 - X_i) \sim \mathcal{B}(q)$ .

$$\begin{aligned}\text{Let, } Z &= \sum_{i=1}^{i=n} Z_i \\ &= \sum_{i=1}^{i=n} (1 - X_i) \\ &= \sum_{i=1}^{i=n} (1) - \sum_{i=1}^{i=n} (X_i) \\ &= n - X.\end{aligned}$$

$$\begin{aligned}\therefore M_Z(t) &= \prod_{i=1}^{i=n} M_{Z_i}(t) \\ &= \prod_{i=1}^{i=n} (p + qe^t) \\ &= (p + qe^t)^n\end{aligned}$$

This shows that-

$$Z \sim b(n, q) \sim b(n, 1 - p)$$

So, we can conclude that option ④ is correct.

**Hence, the correct options are : ① and ④.**