



STATISTICS-I,II FOR PGTRB

Collection of results and problems

Professor Academy

Chennai

This version of the notes is updated on March 16, 2021.

Contents

1 Normal Distribution

2



Standard distributions

1 Normal Distribution

Definition 1.1. A random variable X is said to have a **normal distribution with parameters μ (called "mean") and σ^2 (called "variance")** if its density function is given by the probability law:

$$f(x; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp \left[-\frac{1}{2} \left\{ \frac{x - \mu}{\sigma} \right\}^2 \right]$$
$$\text{or } f(x; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2}$$
$$-\infty < x < \infty, -\infty < \mu < \infty, \sigma > 0$$

In symbol, we write $X \sim N(\mu, \sigma^2)$.

Definition 1.2. If $X \sim N(\mu, \sigma^2)$, then $Z = \frac{X-\mu}{\sigma}$, is a **standard normal variate** with $E(Z) = 0$ and $\text{Var}(Z) = 1$ and we write $Z \sim N(0, 1)$.

The p.d.f. of standard normal variate Z is given by

$$\varphi(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}, -\infty < z < \infty$$

and the corresponding distribution function, denoted by $\Phi(z)$ is given by

$$\begin{aligned} \Phi(z) &= P(Z \leq z) = \int_{-\infty}^z \varphi(u) du \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-u^2/2} du \end{aligned}$$

The definite integral

$$\phi(z) = \int_0^{z_1} \varphi(u) du$$

is known as **normal probability integral** and gives the area under standard normal curve between the ordinates at $Z = 0$ and $Z = z_1$.

Remark 1.3. $\Phi(z)$ has the following important properties:



- $\Phi(-z) = 1 - \Phi(z)$
- whenever $X \sim N(\mu, \sigma^2)$, $P(a \leq X \leq b) = \Phi\left(\frac{b-\mu}{\sigma}\right) - \Phi\left(\frac{a-\mu}{\sigma}\right)$
- The graph of $f(x)$ is a famous 'bell - shaped' curve. The top of the bell is directly above the mean μ . For large values of σ , the curve tends to flatten out and for small values of σ , it has a sharp peak.

Theorem 1.4. Normal Distribution as a Limiting form of Binomial Distribution. Normal distribution is another limiting form of the binomial distribution under the following conditions :

- (i) n , the number of trials is indefinitely large, i.e., $n \rightarrow \infty$ and
- (ii) neither p nor q is very small.

NOTE: Stirlings approximation is used in the proof.

the standard binomial variate:

$$Z = \frac{X - E(X)}{\sqrt{V(X)}} = \frac{X - np}{\sqrt{npq}}; X = 0, 1, 2, \dots, n$$

follows $N(0, 1)$ as $n \rightarrow \infty$.

Remark 1.5. Characteristics of the Normal Distribution and Normal Probability Curve:

- The curve is bell shaped and symmetrical about the line $x = \mu$.
- Mean, median and mode of the distribution coincide
- As x increases numerically, $f(x)$ decreases rapidly, the maximum probability occurring at the point $x = \mu$, and given by $[p(x)]_{\max} = \frac{1}{\sigma\sqrt{2\pi}}$.
- $\beta_1 = 0$ and $\beta_2 = 3$
- x -axis is an asymptote to the curve.
- The points of inflexion ($f''(x) = 0$, and $f'''(x) \neq 0$) of the curve are given by

$$\left[x = \mu \pm \sigma, f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-1/2} \right]$$

- $Q.D. : M.D. : S.D. :: \frac{2}{3}\sigma : \frac{4}{5}\sigma : \sigma :: \frac{2}{3} : \frac{4}{5} : 1$
 $\Rightarrow Q.D. : M.D. : S.D. :: 10 : 12 : 15$



- If X and Y are independent standard normal variates, then $U = X + Y$ and $V = X - Y$ are independently distributed, $U \sim N(0, 2)$ and $V \sim N(0, 2)$
- **Bernstein's Theorem. (Converse of above result)** If X and Y are independent and identically distributed random variables with finite variance and if $U = X + Y$ and $V = X - Y$ are independent, then all r.v.'s X, Y, U and V are normally distributed.
- MGF of $X \sim N(\mu, \sigma^2)$ is given by $M_X(t) = e^{\mu t + t^2 \sigma^2 / 2}$, and $X \sim N(0, 1)$ is $\exp(t^2/2)$.
- CGF is $K_X(t) = \log_e M_X(t) = \mu t + \frac{t^2 \sigma^2}{2}$.
- For the normal distribution all **odd order moments about mean vanish** and the **even order moments about mean** are given by the **recurrence relation**: $\mu_{2n} = \sigma^2(2n-1)\mu_{2n-2}$.
Thus $\mu_{2n} = 1.3.5 \dots (2n-1)\sigma^{2n}$.
- **A linear combination of independent normal variates is also a normal variate:** Let $X_i, (i = 1, 2, \dots, n)$ be n independent normal variates with mean μ_i and variance σ_i^2 respectively. Then

$$\sum_{i=1}^n a_i X_i \sim N \left[\sum_{i=1}^n a_i \mu_i, \sum_{i=1}^n a_i^2 \sigma_i^2 \right]$$

So, $X_1 + X_2 \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$ and $X_1 - X_2 \sim N(\mu_1 - \mu_2, \sigma_1^2 + \sigma_2^2)$.

- The definite integral $\phi(z) = \int_0^z \varphi(z) dz$ is known as **normal probability integral** and gives the area under standard normal curve between the ordinates at $Z = 0$ and $Z = z_1$.
- (i) $P(\mu - \sigma < X < \mu + \sigma) = P(-1 < Z < 1) = 2 \times 0.3413 = 0.6826$, (ii) $P(\mu - 2\sigma < X < \mu + 2\sigma) = 0.9544$ and (iii) $P(\mu - 3\sigma < X < \mu + 3\sigma) = 0.9973$

Problem 1.6. If $X \sim N(50, 10)$ and $Y \sim N(60, 6)$ are independent then $Y - X$ is
A) $N(10, 16)$ B) $N(-10, 16)$ C) $N(10, 4)$ D) $N(10, -4)$

Problem 1.7. If X is normally distributed with mean 2 and variance 1 then $P(|X - 2| < 1)$ is

A) 0.3413 B) 0.6826 C) 0.0228 D) 0.4772



Example 1.8. For a certain normal distribution, the first moment about 10 and the fourth moment about 50 is 48. What is the arithmetic mean and standard deviation of the distribution ?

Solution. We know that if μ'_1 is the first. moment about the point $X = A$ then arithmetic mean is given by:

$$\text{Mean} = A + \mu'_1$$

We are given μ'_1 (about the point $X = 10$) = 40 \Rightarrow Mean = 10 + 40 = 50 Also we are given μ'_4 (about the point $X = 50$) = 48, i.e., $\mu_4 = 48$

$$(\because \text{Mean} = 50)$$

But for a normal distribution with standard deviation σ , $\mu_4 = 3\sigma^4 \Rightarrow 3\sigma^4 = 48$
i.e., $\sigma = 2$

Example 1.9. X is normally distributed and the mean of X is 12 and S.D. is 4. Find out the probability of the following :

(i) $X \geq 20$ (ii) $X \leq 20$, and (iii) $0 \leq X \leq 12$

Soln:

$$(i) P(X \geq 20) = ?$$

$$\text{When } X = 20, \quad Z = \frac{20 - 12}{4} = 2$$

$$\therefore P(X \geq 20) = P(Z \geq 2) = 0.5 - P(0 \leq Z \leq 2) = 0.5 - 0.4772 = 0.0228$$

$$(ii) P(X \leq 20) = 1 - P(X \geq 20) \\ = 1 - 0.0228 = 0.9772$$

$$(iii) P(0 \leq X \leq 12) = P(-3 \leq Z \leq 0) \\ = P(0 \leq Z \leq 3) = 0.49865$$

Example 1.10. X is a normal variate with mean 30 and S.D. 5. Find the probabilities that

(i) $26 \leq X \leq 40$ (ii) $X \geq 45$, and (iii) $|X - 30| > 5$. Given $\phi(0.8) = 0.2881$, $\phi(2) = 0.4772$, $\phi(3) = 0.49865$, $\phi(1) = 0.3413$.

(ANS: (i) 0.7653, (ii) 0.00135, (iii) 0.3174)

Problem 1.11. Two independent random variates X and Y are both normally distributed with means 1 and 2 and standard deviation 3 and 4 respectively. If $Z = X - Y$, then find the median, s.d. and mean of the distribution of Z . Find $P(Z + 1 \leq 0)$.



Problem 1.12. Which of the following is not true about normal distribution?

- A) median is equidistant from Q_1 and Q_3 .
- B) the sum of two independent standard normal Variate is a standard normal Variate
- C) The points of inflexion are at $\mu \pm \sigma$
- D) Curve is symmetrical about mode

Problem 1.13. If the quartile deviation of a normal distribution is 15, then its mean deviation about mean is

- A) 12 B) 10 C) 18 D) 15

Example 1.14. Let $X \sim N(\mu, \sigma^2)$. If $\sigma^2 = \mu^2, (\mu > 0)$, express $P(X < -\mu \mid X < \mu)$ in terms of cumulative distribution function of $N(0, 1)$.

Soln:
$$P(X < -\mu \mid X < \mu) = \frac{P(X < -\mu \cap X < \mu)}{P(X < \mu)} = \frac{P(X < -\mu)}{P(X < \mu)} = \frac{P(Z < -2)}{P(Z < 0)} \quad \left(Z = \frac{X - \mu}{\sigma} = \frac{X - \mu}{\mu} \right)$$
$$= \frac{P(Z > 2)}{P(Z < 0)} = 2[1 - P(Z \leq 2)] = 2[1 - \Phi(2)]$$

Problem 1.15. If a continuous RV X follows $N(0, 4)$, find $P\{1 \leq X \leq 2\}$ and $P\{1 \leq X \leq 2/X \geq 1\}$.

Given $\phi(1) = 0.3413, \phi(0.5) = 0.1915$.

(ANS: 0.1498, 0.4856)

Definition 1.16. If the discrete RV X can take the values $0, 1, 2, \dots$, such that $P(X = i) = (n + i - 1)C_i p^n q^i, i = 0, 1, 2, \dots$, where $p + q = 1$, then X is said to follow a **Pascal (or negative binomial) distribution** with parameter n .

If the pdf of a continuous RV X is $f(x) = \frac{1}{\Gamma(n)} e^{-x} x^{n-1}, 0 < x < \infty$ and $n > 0$, then X follows a **gamma distribution** with parameter n . **Gamma distribution is a particular case of Erlang distribution**, the pdf of which is $f(x) = \frac{c^n}{\Gamma(n)} x^{n-1} e^{-cx}, 0 < x < \infty, n > 0, c > 0$

An Erlang distribution with $n = 1$ [i.e., $f(x) = ce^{-cx}, 0 < x < \infty, c > 0$] is called an **exponential (or negative exponential) distribution** with parameter c .

If the pdf of a continuous RV X is $f(x) = \frac{\alpha}{\pi} \times \frac{1}{x^2 + \alpha^2}, \alpha > 0, -\infty < x < \infty$, then X follows a **Cauchy distribution** with parameter α .

The continuous random variable which is distributed according to the probability



law

$$f(x) = \begin{cases} \frac{1}{B(\mu, v)} \cdot x^{\mu-1} (1-x)^{v-1}; (\mu, v) > 0, 0 < x < 1 \\ 0, \text{ otherwise} \end{cases}$$

(where $B(\mu, v)$ is the Beta function), is known as a **Beta variate of the first kind** with parameters μ and v and is referred to as $\beta_1(\mu, v)$ variate and its distribution is called **Beta distribution of the first kind**.

The continuous random variable X which is distributed according to the probability law

$$f(x) = \begin{cases} \frac{1}{B(\mu, v)} \cdot \frac{x^{\mu-1}}{(1+x)^{\mu+v}}; (\mu, v) > 0, 0 < x < \infty \\ 0, \text{ otherwise} \end{cases}$$

is known as a **Beta variate of second kind** with parameters' μ and v and is denoted as $\beta_2(\mu, v)$ variate and its distribution is called **Beta distribution of second kind**.

The probability that E_1 occurs x_1 times, E_2 occurs x_2 times ... and E_k occurs x_k times in n independent observations, is given by

$$p(x_1, x_2, \dots, x_k) = \frac{n!}{x_1! x_2! \dots x_k!} p_1^{x_1} p_2^{x_2} \dots p_k^{x_k}$$

where $\sum x_i = n$ is known as **Multinomial distribution**.