

UNIT- 4

PROBABILITY DISTRIBUTIONS

Let 'S' be a sample space of a random experiment.

Suppose to each

element s of 'S', a unique real number X is associated according to some rule.

Then X , is called a random variable on S.

Example:

Consider a random experiment of tossing three coins together.

The corresponding sample space is

$S = \{HHH, HHT, HTH, THH, HTT, THT, TTH, TTT\}$
which has 8 possible outcomes.

Suppose we define the mapping $f: S \rightarrow R$ by $f(s)$ = number of heads in an outcome s i.e.,

$f(HHH)=3, f(HHT)=2, f(HTH)=2, f(THH)=2, f(HTT)=1, f(TTH)=1, f(TTT)=0$

As s varies over the set S , X varies over the set $\{0,1,2,3\}$ belongs to R .

Note: One can define infinitely many random variable on a given sample space.

Discrete Random Variables:

A random variable which can take some specified values only is called as Discrete Random Variables.
(Varying only over integral values)

Ex: Tossing a coin and observing the number of heads turning up.

Several white lines of varying lengths and slopes are drawn in the bottom right corner of the slide, creating a modern, abstract design element.

Continuous Random Variables:

A random variable which can take any value in a specified range is called Continuous Random Variable.

(can assume any value in the interval of real numbers)

Example: Speed ,time etc.....

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Discrete Probability Distributions:

If for each value x_i of a discrete random variable X , a real number $p(x_i)$ is assigned such that

- a) $p(x_i) \geq 0$

- b) $\sum_i p(x_i) = 1$

Then the function $p(x)$ is called Probability Function

The set of values $[x_i, p(x_i)]$ is called a discrete probability distribution of discrete random variable X .

The function $p(x)$ is called the probability density function(pdf).

The distribution function $f(x)$ is defined by $f(x) = P(X \leq x) = \sum_{i=1}^x p(x_i)$, x being an integer is called the cumulative distribution function(cdf).

Note:

$$\text{Mean}(\mu) = \sum_i x_i \cdot p(x_i)$$


$$\begin{aligned}\text{Variance } (V) &= \sum_i (x_i - \mu)^2 \cdot p(x_i) \\ &= \sum x_i^2 \cdot p(x_i) - \mu^2\end{aligned}$$

$$\text{Standard deviation}(\sigma) = \sqrt{V}$$

Discrete Probability Distribution

Binomial distribution:

It is concerned with trials of repetitive nature in which only the occurrence or non-occurrence, success or failure, acceptance or rejection ,yes or no of a particular event is of interest.

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It is a discrete distribution which satisfy the following conditions:

- i) Each trail has two mutually exclusive possible outcomes.
- ii) Each trail is independent of the other trails.
- iii) The probability of success p or failure q remains constant from trail to trail.
- iv) The trails are performed under the same conditions for fixed number of times ,say ' n '.

If a series of independent trials are performed such that for each trial, p is the probability of success and q is the probability of failure, then the probability of x successes in a series of n trials is given by,

$${}^nC_x p^x q^{n-x}, \text{ where } x=0,1,2,3,\dots,n$$

$$\text{That is., } p(x) = {}^nC_x p^x q^{n-x}$$

Mean, Standard deviation and Variance of Binomial Distributions:

$$\textit{Mean}(\mu) = np$$

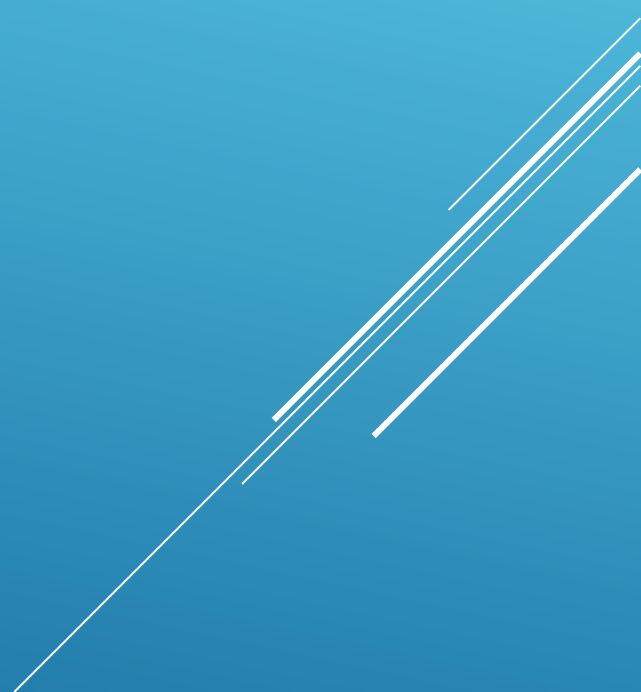
$$\textit{Variance}(V) = npq$$

$$\textit{Standard deviation}(\sigma) = \sqrt{npq}$$

Poission Distribution

It is a distribution related to the probability of events which are extremely rare, but which have a large number of independent oppurtunities for occurance.

This can be derived as a limiting case of the Binomial Distribution by making **n** very large and **p** very small keeping **np** fixed.



Poission Probability Function:

$$p(x) = \frac{m^x e^{-m}}{x!} \quad \text{for } x=0,1,2,3,\dots$$

Mean and Standard Deviation:

$$\text{Mean}(\mu) = m$$

$$\text{Variance}(V) = m$$

$$\text{Standard deviation}(\sigma) = \sqrt{m}$$

Continuous Probability Distribution:

Definition:

If for every 'x' belonging to the range of continuous random variable X, we assign a real number f(x) satisfying the conditions

$$a) f(x) \geq 0 \quad b) \int_{-\infty}^{\infty} f(x)dx = 1$$

Then f(x) is called a continuous probability function or probability density function.

If (a, b) is a sub interval of the range space of X then the probability that ' x ' lies in (a,b) is defined to be a integral of $f(x)$ between a and b .

that is.,
$$P(a \leq x \leq b) = \int_a^b f(x) dx$$

Cumulative Distribution Function:

If X is a continuous random variable with pdf $f(x)$ then the function $F(x)$ defined by $\mathbf{F(x) = P(X \leq x) = \int_{-\infty}^x f(x)dx}$ is called cumulative distribution function (c d f) of X .

NOTE: $F(x) = P(X \leq x) = P(-\infty \leq x \leq x)$

$$\text{and } \frac{d[F(x)]}{dx} = f(x)$$

NOTE:

1) $\int_{-\infty}^{\infty} f(x)dx = 1$; geometrically means that the area bounded by the curve $f(x)$ and x axis is equal to unity.

2) $P(a \leq x \leq b)$
is equal to area of the region bounded by the curve $f(x)$, the x - axis and the co - ordinates $x = a$ and $x = b$.

3) $P(a \leq x \leq b) =$
 $\int_a^b f(x)dx = \int_{-\infty}^b f(x)dx - \int_{-\infty}^a f(x)dx = F(b) - F(a)$

4) If r is any real no. then,

$$P(x \geq r) = \int_r^{\infty} f(x)dx;$$

$$P(x < r) = 1 - P(x \geq r)$$

Mean and Variance:

$$\text{Mean}(\mu) = \int_{-\infty}^{\infty} xf(x)dx$$

Variance(v)=

$$\int_{-\infty}^{\infty} (x - \mu)^2 f(x)dx = \int_{-\infty}^{\infty} x^2 f(x)dx - \mu^2$$

Exponential Distribution

(14)

Probability density function is

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & \text{for } x > 0 \\ 0 & \text{otherwise, where } \lambda > 0. \end{cases}$$

Mean & S.D:

$$\text{Mean } (\mu) = \int_{-\infty}^{\infty} x f(x) dx = \int_{-\infty}^{\infty} x \cdot \lambda e^{-\lambda x} dx.$$

Using Bernoulli's rule

$$\mu = \lambda \left[x \cdot \left(\frac{e^{-\lambda x}}{-\lambda} \right) - 1 \left(\frac{e^{-\lambda x}}{\lambda^2} \right) \right]_0^{\infty}$$

$$= \lambda \left[0 \cdot \frac{1}{\lambda^2} (0 - 1) \right] = \frac{1}{\lambda}$$

$$\therefore \mu = \frac{1}{\lambda}.$$

$$\begin{aligned} \text{Var} &= \int_{-\infty}^{\infty} (x - \mu)^2 f(x) dx \\ &= \int_{-\infty}^{\infty} (x - \mu)^2 x \cdot \lambda e^{-\lambda x} dx \\ &= \lambda \int_0^{\infty} (x - \mu)^2 e^{-\lambda x} dx \end{aligned}$$

Applying Bernoulli's rule

$$\begin{aligned} &= \lambda \left[(x - \mu)^2 \left[\frac{e^{-\lambda x}}{-\lambda} \right] - 2(x - \mu) \cdot \left[\frac{e^{-\lambda x}}{\lambda^2} \right] + 2 \left[\frac{e^{-\lambda x}}{-\lambda^3} \right] \right]_0^{\infty} \\ &= \lambda \left[-\frac{1}{\lambda} (0 - \mu)^2 - \frac{2}{\lambda^2} (0 - (-\mu)) - \frac{2}{\lambda^3} (0 - 1) \right] \end{aligned}$$

$$= \alpha \left\{ \frac{\mu^2}{\alpha} - \frac{2\mu}{\alpha^2} + \frac{2}{\alpha^3} \right\} \quad \text{But } \mu = \frac{1}{\alpha}$$

$$\sigma^2 = \alpha \left\{ \frac{1}{\alpha^3} - \frac{2}{\alpha^3} + \frac{2}{\alpha^3} \right\} = \frac{1}{\alpha^2}$$

$$\sigma = \frac{1}{\alpha}$$

$$\text{mean}(\mu) = \frac{1}{\alpha} \quad ; \quad \text{S.D}(\sigma) = \frac{1}{\alpha}$$

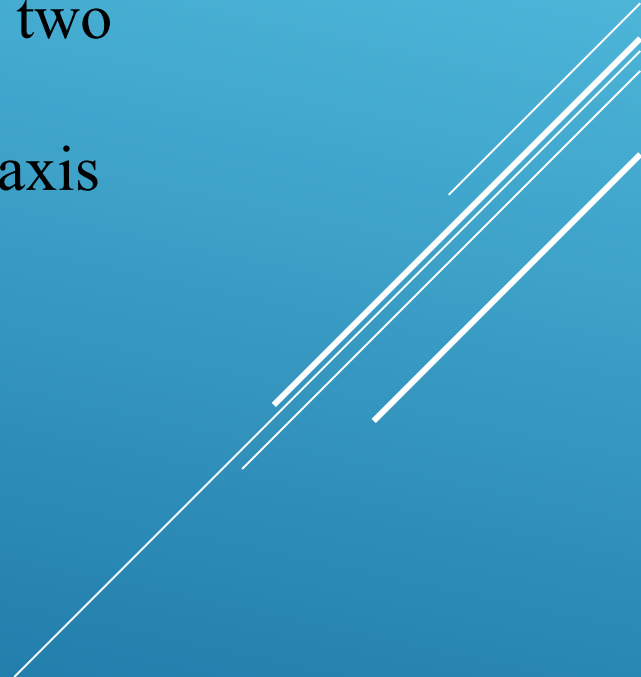
Normal Distribution:

The pdf $f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

Where variable x assumes all the values from $-\infty$ to ∞ ;

μ and σ are called the parameters of the equation, respectively the mean and the standard deviation of the distribution.

Basic Properties:

- a) The area under the normal curve is 1
 - b) The normal distribution is symmetric about the mean.
 - c) The graph of the normal distribution is called the normal curve. It is bell shaped and symmetric about the mean. The two tails of the curve extend to $-\infty$ and ∞ towards positive and negative directions of x-axis and gradually approach the x-axis without ever meeting it.
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Mean and Standard Deviation of Normal Distribution:

$$\text{Mean}(\mu) = \mu$$

That is., the mean of the normal distribution is equal to the mean of the given distribution.

$$\text{Variance}(V) = \sigma^2$$

That is., the Variance of the normal distribution is equal to the Variance of the given distribution.

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Standard Normal Distribution:

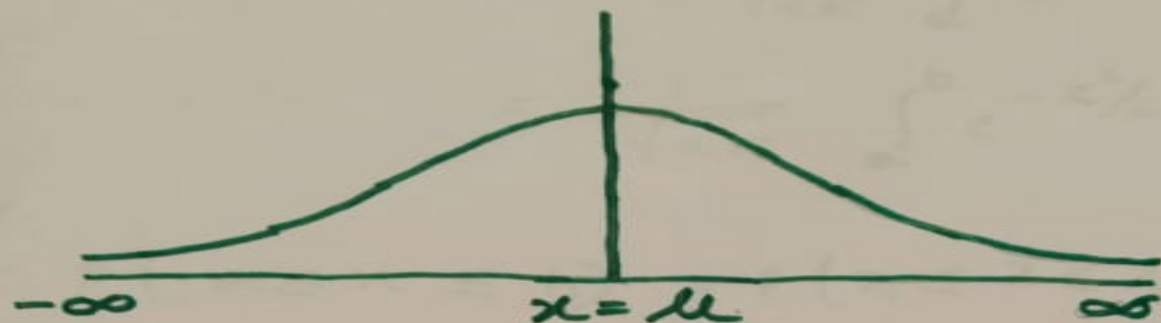
The Normal Distribution for which the mean is zero and the standard deviation is 1 is called the Standard Normal Distribution.

The density function for the standard normal distribution is.,

$$\phi(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}$$

Normal Curve

31



The graph of the prob. func $f(x)$ is bell shaped curve symmetrical about the line $x = \mu$ and is called normal probability curve.

Standard Normal Distribution

We have
$$P(a \leq x \leq b) = \int_a^b f(x) dx$$

For normal distⁿ we have

$$P(a \leq x \leq b) = \frac{1}{\sigma\sqrt{2\pi}} \int_a^b e^{-(x-\mu)^2/2\sigma^2} dx \quad \text{--- (1)}$$

Put $z = \frac{x-\mu}{\sigma}$ or $x = \mu + \sigma z$ then $dx = \sigma dz$

Let $z_1 = \frac{a-\mu}{\sigma}$ & $z_2 = \frac{b-\mu}{\sigma}$ be the values of z corresponding to $x=a$ & $x=b$ then

(1) becomes

$$P(a \leq x \leq b) = \frac{1}{\sigma \sqrt{2\pi}} \int_a^b e^{-z^2/2} \sigma dz$$

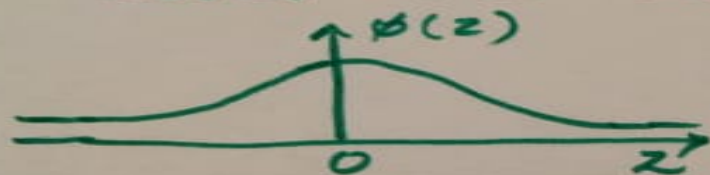
$$= \frac{1}{\sqrt{2\pi}} \int_a^b e^{-z^2/2} dz$$

33

$$\therefore P(a \leq x \leq b) = P(z_1 \leq z \leq z_2) = \frac{1}{\sqrt{2\pi}} \int_{z_1}^{z_2} e^{-z^2/2} dz.$$

$\therefore z = \frac{x-\mu}{\sigma}$ is known as the $\overset{F(z)}{\text{standard}}$ normal variate (SNV) with $\mu=0, \sigma=1$.

The $F(z)$ is SNV which is symmetrical about the line $z=0$



The integral in RHS represent the area bounded by $z=z_1$ and $z=z_2$. Further if $z_1=0$ we have

$$\phi(z) = \frac{1}{\sqrt{2\pi}} \int_0^z e^{-z^2/2} dz \text{ represent the area from } z=0 \text{ to } z$$

