

# 1. Introduction

Welcome to the series of E-learning module on normal distribution.

By the end of this session, you will be able to:

- Explain the normal distribution
- Explain the distribution function  $\Phi$  of  $Z$
- Explain the limiting case of other distributions
- Explain mode and median of the distribution
- Explain Moment Generating Function (mgf), Cumulant Generating Function (cgf), Skewness and Kurtosis
- Explain the moments
- Explain the points of inflexion and mean deviation
- Explain the distribution of linear combination of normal variates

A random variable  $X$  is said to follow normal distribution with parameters  $\mu$  and  $\sigma^2$  if its probability density function is given by,  
 $f(x)$  is equal to  $\frac{1}{\sigma \sqrt{2\pi}}$   $e^{-\frac{(x-\mu)^2}{2\sigma^2}}$ ,  $x$  lies between minus infinity to infinity,  $\mu$  lies between minus infinity to infinity and  $\sigma$  is greater than zero.

Now, consider the following remarks:

1. When a random variable is normally distributed with mean  $\mu$  and standard deviation  $\sigma$ , it is customary to write  $X$  is distributed as Normal ( $\mu, \sigma^2$ ) and is expressed by  $X$  follows Normal ( $\mu, \sigma^2$ ).

2. If  $X$  follows Normal ( $\mu, \sigma^2$ ), then  $Z$  is equal to  $X - \mu$  divided by  $\sigma$  is a standard normal variate with expectation of  $Z$  is equal to zero and Variance of  $Z$  is equal to 1 and we write  $Z$  follows normal zero, 1.

3. The probability density function of standard normal variate  $Z$  is given by,  
 $f(z)$  is equal to  $\frac{1}{\sqrt{2\pi}}$   $e^{-\frac{z^2}{2}}$ ,  $z$  lies between minus infinity to infinity and corresponding distribution function is given by,  $\Phi(z)$  is equal to probability that  $Z$  is less than or equal to  $z$  is equal to  $\frac{1}{\sqrt{2\pi}}$  integral from minus infinity to  $z$   $e^{-\frac{z^2}{2}}$   $dz$ .

4. The graph of  $f(x)$  is a famous bell-shaped curve. The top of the bell is directly above the mean  $\mu$ . For large values of  $\sigma$ , the curve tends to flatten out and for small values of  $\sigma$ , it has a sharp peak.

We shall prove two important results on the distribution function  $\Phi$  of standard normal variate.

The first one is,

$\Phi(-z)$  is equal to  $1 - \Phi(z)$ , where  $z$  is greater than zero

To prove this, consider the left hand side,

$\Phi(-z)$  is equal to probability that  $Z$  is less than or equal to minus  $Z$

Is equal to probability that  $Z$  is greater than or equal to  $z$  (because of symmetry about zero)

Is equal to  $1 - \text{probability that } z \text{ is less than or equal to } z$ .

Is equal to  $1 - \Phi(z)$ .

The second result is,

Probability that  $a \leq X \leq b$  is equal to  $\Phi\left(\frac{b - \mu}{\sigma}\right) - \Phi\left(\frac{a - \mu}{\sigma}\right)$ , where  $X$  follows normal  $\mu, \sigma^2$ .

To prove this, consider probability that  $a \leq X \leq b$

Is equal to probability that  $\frac{a - \mu}{\sigma} \leq Z \leq \frac{b - \mu}{\sigma}$ , where  $Z$  is equal to  $\frac{X - \mu}{\sigma}$

Is equal to probability that  $Z$  is less than or equal to  $\frac{b - \mu}{\sigma}$  minus probability that  $Z$  is less than or equal to  $\frac{a - \mu}{\sigma}$

Is equal to  $\Phi\left(\frac{b - \mu}{\sigma}\right) - \Phi\left(\frac{a - \mu}{\sigma}\right)$ .

In the previous modules, we have already discussed the chief characteristics and properties of Normal Distribution. We have stated that most of the distributions tend to normal distribution.

For example, Binomial Distribution, which is discrete, tends to normal distribution under the following conditions:

- $n$ , the number of trials is indefinitely large, that is as  $n$  tends to infinity
- Neither  $p$  nor  $q$  is very small

Poisson distribution tends to normal distribution, when the parameter  $\lambda$  tends to infinity.

Gamma distribution tends to normal distribution for large values of  $\alpha$ .

## 2. Mode and Median

Mode is the value of  $x$  for which  $f$  of  $(x)$  is maximum that is, mode is the solution of  $f$  dash of  $(x)$  is equal to zero and  $f$  double dash of  $(x)$  is less than zero.

For normal distribution with mean  $\mu$  and standard deviation  $\sigma$ ,

$\log f$  of  $x$  is equal to  $c$  minus  $\frac{1}{2}$  into  $\sigma^2$  into  $x$  minus  $\mu$  whole square, where  $c$  is equal to  $\log \frac{1}{\sigma \sqrt{2\pi}}$ , a constant.

Differentiating with respect to  $x$  we get,

$\frac{1}{f} \frac{df}{dx}$  is equal to  $\frac{1}{\sigma^2} (x - \mu)$

$\frac{df}{dx}$  is equal to  $\frac{1}{\sigma^2} (x - \mu) f$

and  $\frac{d^2f}{dx^2}$  is equal to  $-\frac{1}{\sigma^2} f$

By substituting for  $\frac{df}{dx}$ , we get,

$\frac{d^2f}{dx^2} = -\frac{1}{\sigma^2} f$

By equating  $\frac{df}{dx}$  is equal to zero, we get,  $x - \mu = 0$  implies,  $x$  is equal to  $\mu$ .

At the point  $x$  is equal to  $\mu$ , we have

$\frac{d^2f}{dx^2}$  is equal to  $-\frac{1}{\sigma^2} f$  at  $x$  is equal to  $\mu$ ,

is equal to  $-\frac{1}{\sigma^2} f$  at  $x = \mu$ , which is less than zero

Hence,  $x$  is equal to  $\mu$  is the mode of the normal distribution.

Now, let us obtain median of the normal distribution.

If  $M$  is the median of the normal distribution, we have,

$\int_{-\infty}^M f(x) dx = \frac{1}{2}$

Implies,  $\frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^M e^{-\frac{x^2 - 2x\mu + \mu^2}{2\sigma^2}} dx = \frac{1}{2}$

By splitting the range from  $-\infty$  to  $M$  as  $-\infty$  to  $\mu$  and from  $\mu$  to  $M$ , we get

$\frac{1}{\sigma \sqrt{2\pi}} \left[ \int_{-\infty}^{\mu} e^{-\frac{x^2 - 2x\mu + \mu^2}{2\sigma^2}} dx + \int_{\mu}^M e^{-\frac{x^2 - 2x\mu + \mu^2}{2\sigma^2}} dx \right] = \frac{1}{2}$

But  $\frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\mu} e^{-\frac{x^2 - 2x\mu + \mu^2}{2\sigma^2}} dx = \frac{1}{2}$

By substituting  $z = \frac{x - \mu}{\sigma}$ , we get,

$\frac{1}{\sqrt{2\pi}} \int_{-\infty}^0 e^{-\frac{z^2}{2}} dz = \frac{1}{2}$

Hence, by substitution we get,

$\frac{1}{\sigma \sqrt{2\pi}} \int_{\mu}^M e^{-\frac{x^2 - 2x\mu + \mu^2}{2\sigma^2}} dx = \frac{1}{2}$

Implies  $\frac{1}{\sigma \sqrt{2\pi}} \int_{\mu}^M e^{-\frac{x^2 - 2x\mu + \mu^2}{2\sigma^2}} dx = 0$

That is  $\mu$  is equal to  $M$

Hence, for normal distribution Mean is equal to Median is equal to Mode is equal to  $\mu$ .

### 3. MGF, CGF, Skewness, Kurtosis and Moments

The moment generating function is given by,

$M_X(t)$  is equal to  $\int_{-\infty}^{\infty} e^{tx} f(x) dx$

Is equal to  $\frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\infty} e^{tx} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} dx$

Is equal to  $\frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\infty} e^{t(\mu + z\sigma)} e^{-\frac{1}{2}z^2} dz$ , where  $z$  is equal to  $\frac{x-\mu}{\sigma}$

Is equal to  $e^{t\mu} \frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}z^2 + 2tz\sigma} dz$

Is equal to  $e^{t\mu} \frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}(z - t\sigma)^2 + \frac{1}{2}t^2\sigma^2} dz$

Is equal to  $e^{t\mu} \frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}z^2} dz e^{\frac{1}{2}t^2\sigma^2}$

Is equal to  $e^{t\mu} e^{\frac{1}{2}t^2\sigma^2} \frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}z^2} dz$ , where  $u$  is equal to  $z - t\sigma$

Is equal to  $e^{t\mu} e^{\frac{1}{2}t^2\sigma^2}$

Let us obtain Moment generating function of standard normal variate: If  $X$  follows Normal distribution with parameters  $(\mu, \text{and } \sigma^2)$ , then standard normal variate is,  $Z$  is equal to  $\frac{(X - \mu)}{\sigma}$  and its moment generating function is given by,

$M_Z(t)$  is equal to  $e^{t\mu/\sigma} M_X(t/\sigma)$

Is equal to  $e^{t\mu/\sigma} e^{\frac{1}{2}(t/\sigma)^2\sigma^2}$

Is equal to  $e^{t\mu + \frac{1}{2}t^2\sigma}$

Cumulant generating function is given by,  $K_X(t)$  is equal to  $\log M_X(t)$

Is equal to  $\log e^{t\mu + \frac{1}{2}t^2\sigma} = t\mu + \frac{1}{2}t^2\sigma$

Is equal to  $t\mu + \frac{1}{2}t^2\sigma$

Thus,  $K_1$  is equal to  $\mu$ , the mean

$K_2$  is equal to  $\sigma$ , the variance

$K_3$  is equal to zero and  $K_4$  is equal to zero and hence  $\mu_4$  is equal to  $k_4 + 3\sigma^2$  square is equal to  $3\sigma^4$ .

Thus,  $\beta_1$  is equal to  $\frac{\mu_3^2}{\mu_2^3}$  is equal to zero and  $\beta_2$  is equal to  $\frac{\mu_4}{\mu_2^2}$  is equal to 3.

Hence, normal distribution is symmetric and has a normal curve or mesokurtic curve.

Now, let us obtain the moments of the normal distribution.

It can be easily obtained by using moment generating function about mean.

We know that,  $M_X(t)$  is equal to  $e^{t\mu + \frac{1}{2}t^2\sigma}$

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Implies,  $MX - \mu$  of  $t$  is equal to  $e^{\mu - t}$  into  $MX$  of  $t$

Is equal to  $e^{\mu - t}$  into  $\mu$  plus  $t$  square into sigma square divided by 2

Is equal to  $e^{\mu - t}$  square into sigma square divided by 2

Is equal to  $1 + t$  square into sigma square divided by 2 plus  $t$  square into sigma square divided by  $2^2$  factorial plus  $t$  square into sigma square divided by  $2^3$  factorial plus up to plus  $t$  square into sigma square divided by  $2^n$  factorial plus etc.

The coefficient of  $t^r$  divided by  $r$  factorial in the above expression gives  $\mu_r$ , the  $r^{\text{th}}$  moment about mean. Since there is no term with odd power of  $t$  in the above expression, all odd order moments about mean vanish.

That is,  $\mu_{2n+1}$  is equal to zero for  $n$  is equal to 1, 2, etc.

and  $\mu_{2n}$  is equal to coefficient of  $t^{2n}$  divided by  $2n$  factorial.

Is equal to sigma power  $2n$  into  $2n$  factorial divided by  $2^n$  into  $n$  factorial

By expanding  $2n$  factorial we get,

Sigma power  $2n$  divided by  $2^n$  into  $n$  factorial into  $2n$  into  $2n-1$  into  $2n-2$  into  $2n-3$  into up to into 5 into 4 into 3 into 2 into 1.

By separating odd and even terms in the above we get

Sigma power  $2n$  divided by  $2^n$  into  $n$  factorial into  $1 \times 3 \times 5 \times \dots \times (2n-1)$  into  $2 \times 4 \times 6 \times \dots \times 2n$

By taking common 2 in the last term we get,

Sigma power  $2n$  divided by  $2^n$  into  $n$  factorial into  $1 \times 3 \times 5 \times \dots \times (2n-1)$  into  $2^n$  into  $1 \times 2 \times 3 \times \dots \times n$

On simplification we get,

$1 \times 3 \times 5 \times \dots \times (2n-1)$  into sigma power  $2n$

# 4. Points of Inflexion and Mean Deviation

At the point of inflexion of the normal curve, we should have  $f''(x)$  is equal to zero and  $f'''(x)$  is not equal to zero.

From the solution of mode, we have,

$f''(x)$  is equal to  $-\frac{f(x)}{\sigma^2} \left(1 + \frac{(x - \mu)^2}{\sigma^2}\right)$

$f''(x)$  is equal to zero implies,

$1 + \frac{(x - \mu)^2}{\sigma^2} = 0$

Implies,  $x = \mu \pm \sigma$ .

It can be easily verified that the points  $x = \mu \pm \sigma$ ,  $f'''(x)$  is not equal to zero. Hence, the points of inflexion of the normal curve are given by  $\mu \pm \sigma$

For a normal distribution, we know that mean is equal to median is equal to mode is equal to  $\mu$ . Hence, mean deviation at  $\mu$  is given by,

M.D is equal to  $\int_{-\infty}^{\infty} |x - \mu| f(x) dx$

Is equal to  $\frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\infty} |x - \mu| e^{-\frac{(x - \mu)^2}{2\sigma^2}} dx$

Is equal to  $\frac{\sigma}{\sqrt{2\pi}} \int_{-\infty}^{\infty} |z| e^{-\frac{z^2}{2}} dz$ , where  $z = \frac{x - \mu}{\sigma}$

Since  $|z|$  and  $e^{-\frac{z^2}{2}}$  are even function, we can write integral from  $-\infty$  to  $\infty$  as 2 times integral from zero to infinity. Hence, we write,

$\frac{2\sigma}{\sqrt{2\pi}} \int_0^{\infty} z e^{-\frac{z^2}{2}} dz$

Since in the interval zero to infinity,  $|z|$  is equal to  $z$ , we have

M.D is equal to  $\frac{\sigma}{\sqrt{2\pi}} \int_0^{\infty} z e^{-\frac{z^2}{2}} dz$

Is equal to  $\frac{\sigma}{\sqrt{2\pi}} \int_0^{\infty} e^{-\frac{t}{2}} dt$  where  $t = \frac{z^2}{2}$

Is equal to  $\frac{\sigma}{\sqrt{2\pi}} \left[ -2e^{-\frac{t}{2}} \right]_0^{\infty}$ , ranges from zero to infinity

Is equal to  $\frac{\sigma}{\sqrt{2\pi}} \times 2$

Or approximately equal to  $\frac{4}{5} \sigma$ .

# 5. Distribution of Linear Combination

Let  $X_i$ ,  $i$  is equal to 1, 2, up to  $n$  be  $n$  independent normal variates with mean  $\mu_i$  and variance  $\sigma_i^2$  respectively. Then,

$M_{X_i}(t)$  is equal to  $e^{\mu_i t + \frac{1}{2} \sigma_i^2 t^2}$

The moment generating function of their linear combination  $\sum_{i=1}^n a_i X_i$ , where  $a_1, a_2, \dots, a_n$  are constants, is given by

$M_{\sum_{i=1}^n a_i X_i}(t)$  is equal to product from  $i=1$  to  $n$  of  $M_{a_i X_i}(t)$ , since  $X_i$ 's are independent.

Is equal to  $M_{X_1}(a_1 t) M_{X_2}(a_2 t) \dots M_{X_n}(a_n t)$ , since  $M_{cX}(t)$  is equal to  $M_X(ct)$

Using mgf of normal distribution, let us obtain mgf of  $\sum_{i=1}^n a_i X_i$  is equal to  $M_{\sum_{i=1}^n a_i X_i}(t)$

Is equal to  $e^{\mu_1 a_1 t + \frac{1}{2} \sigma_1^2 a_1^2 t^2} \dots e^{\mu_n a_n t + \frac{1}{2} \sigma_n^2 a_n^2 t^2}$

Therefore,

$M_{\sum_{i=1}^n a_i X_i}(t)$  is equal to  $(e^{\mu_1 a_1 t + \frac{1}{2} \sigma_1^2 a_1^2 t^2}) \dots (e^{\mu_n a_n t + \frac{1}{2} \sigma_n^2 a_n^2 t^2})$  up to  $(e^{\mu_n a_n t + \frac{1}{2} \sigma_n^2 a_n^2 t^2})$

Is equal to  $e^{\sum_{i=1}^n a_i \mu_i t + \frac{1}{2} \sum_{i=1}^n a_i^2 \sigma_i^2 t^2}$ , which is the mgf of a normal variate with mean  $\sum_{i=1}^n a_i \mu_i$  and variance  $\sum_{i=1}^n a_i^2 \sigma_i^2$ . Hence, by uniqueness theorem of mgf,  $\sum_{i=1}^n a_i X_i$  follows normal distribution with parameters  $\sum_{i=1}^n a_i \mu_i$  and  $\sum_{i=1}^n a_i^2 \sigma_i^2$ .

Here's a summary of our learning in this session, where we have understood:

- The normal distribution
- The distribution function  $\Phi$  of  $Z$
- The limiting case of other distributions
- The mode and median of the distribution
- The mgf, cgf, skewness and kurtosis
- The moments
- The points of inflexion and mean deviation
- The distribution of linear combination of normal variates