

### 3.1 MOMENTS

Moments are statistical tools, used in statistical investigations. The moments of a distribution are the arithmetic means of the various powers of the deviations of items from some given number.

### 3.2 MOMENTS ABOUT MEAN (Central Moments)

#### 3.2.1. For an Individual Series

If  $x_1, x_2, \dots, x_n$  are the values of the variable under consideration, the  $r^{\text{th}}$  moment  $\mu_r$  about mean  $\bar{x}$  is defined as

$$\mu_r = \frac{\sum_{i=1}^n (x_i - \bar{x})^r}{n} ; r = 0, 1, 2, \dots$$

#### 3.2.2. For a Frequency Distribution

If  $x_1, x_2, \dots, x_n$  are the values of a variable  $x$  with the corresponding frequencies  $f_1, f_2, \dots, f_n$  respectively then  $r^{\text{th}}$  moment  $\mu_r$  about the mean  $\bar{x}$  is defined as

$$\mu_r = \frac{\sum_{i=1}^n f_i (x_i - \bar{x})^r}{N} ; r = 0, 1, 2, \dots \quad \text{where } N = \sum_{i=1}^n f_i$$

In particular, 
$$\mu_0 = \frac{1}{N} \sum_{i=1}^n f_i (x_i - \bar{x})^0 = \frac{1}{N} \sum_{i=1}^n f_i = \frac{N}{N} = 1$$

$\therefore$  For any distribution,  $\mu_0 = 1$

For  $r = 1$ ,

$$\mu_1 = \frac{1}{N} \sum_{i=1}^n f_i (x_i - \bar{x}) = \frac{1}{N} \sum_{i=1}^n f_i x_i - \bar{x} \left( \frac{1}{N} \sum_{i=1}^n f_i \right) = \bar{x} - \bar{x} = 0$$

$\therefore$  For any distribution,  $\mu_1 = 0$

For  $r = 2$ ,

$$\mu_2 = \frac{1}{N} \sum_{i=1}^n f_i (x_i - \bar{x})^2 = (\text{S.D.})^2 = \text{Variance}$$

$\therefore$  For any distribution,  $\mu_2$  coincides with the variance of the distribution.

Similarly, 
$$\mu_3 = \frac{1}{N} \sum_{i=1}^n f_i (x_i - \bar{x})^3, \mu_4 = \frac{1}{N} \sum_{i=1}^n f_i (x_i - \bar{x})^4$$

and so on.

**Note.** In case of a frequency distribution with class intervals, the values of  $x$  are the mid-points of the intervals.

### EXAMPLES

**Example 1.** Find the first four moments for the following individual series:

$x$	3	6	8	10	18
-----	---	---	---	----	----

**Sol.**

#### Calculation of Moments

S. No.	$x$	$x - \bar{x}$	$(x - \bar{x})^2$	$(x - \bar{x})^3$	$(x - \bar{x})^4$
1	3	-6	36	-216	1296
2	6	-3	9	-27	81
3	8	-1	1	-1	1
4	10	1	1	1	1
5	18	9	81	729	6561
$n = 5$	$\Sigma x = 45$	$\Sigma(x - \bar{x}) = 0$	$\Sigma(x - \bar{x})^2 = 128$	$\Sigma(x - \bar{x})^3 = 486$	$\Sigma(x - \bar{x})^4 = 7940$

Now, 
$$\bar{x} = \frac{\Sigma x}{n} = \frac{45}{5} = 9$$

$\therefore \mu_1 = \frac{\Sigma(x - \bar{x})}{n} = \frac{0}{5} = 0, \quad \mu_2 = \frac{\Sigma(x - \bar{x})^2}{n} = \frac{128}{5} = 25.6$

$$\mu_3 = \frac{\Sigma(x - \bar{x})^3}{n} = \frac{486}{5} = 97.2, \quad \mu_4 = \frac{\Sigma(x - \bar{x})^4}{n} = \frac{7940}{5} = 1588.$$

**Example 2.** Calculate  $\mu_1, \mu_2, \mu_3, \mu_4$  for the following frequency distribution:

Marks	5-15	15-25	25-35	35-45	45-55	55-65
No. of students	10	20	25	20	15	10



Sol.

## Calculation of Moments

Marks	No. of students (f)	Mid-point (x)	fx	$x - \bar{x}$	$f(x - \bar{x})$	$f(x - \bar{x})^2$	$f(x - \bar{x})^3$	$f(x - \bar{x})^4$
5-15	10	10	100	-24	-240	5760	-138240	3317760
15-25	20	20	400	-14	-280	3920	-54880	768320
25-35	25	30	750	-4	-100	400	-1600	6400
35-45	20	40	800	6	120	720	4320	25920
45-55	15	50	750	16	240	3840	61440	983040
55-65	10	60	600	26	260	6760	175760	4569760
	N = 100		$\Sigma fx$ = 3400		$\Sigma f(x - \bar{x})$ = 0	$\Sigma f(x - \bar{x})^2$ = 21400	$\Sigma f(x - \bar{x})^3$ = 46800	$\Sigma f(x - \bar{x})^4$ = 9671200

$$\text{Now, } \bar{x} = \frac{\Sigma fx}{N} = \frac{3400}{100} = 34$$

$$\therefore \mu_1 = \frac{\Sigma f(x - \bar{x})}{N} = \frac{0}{100} = 0,$$

$$\mu_2 = \frac{\Sigma f(x - \bar{x})^2}{N} = \frac{21400}{100} = 214$$

$$\mu_3 = \frac{\Sigma f(x - \bar{x})^3}{N} = \frac{46800}{100} = 468,$$

$$\mu_4 = \frac{\Sigma f(x - \bar{x})^4}{N} = \frac{9671200}{100} = 96712.$$

## 3.3 SHEPPARD'S CORRECTIONS FOR MOMENTS

While computing moments for frequency distribution with class intervals, we take variable  $x$  as the mid-point of class-intervals which means that we have assumed the frequencies concentrated at the mid-points of class-intervals.

The above assumption is true when the distribution is symmetrical and the no. of class-intervals is not greater than  $\frac{1}{20}$ th of the range, otherwise the computation of moments will have certain error called **grouping error**.

This error is corrected by the following formulae given by **W.F. Sheppard**.

$$\mu_2 (\text{corrected}) = \mu_2 - \frac{h^2}{12}$$

$$\mu_4 (\text{corrected}) = \mu_4 - \frac{1}{2}h^2\mu_2 + \frac{7}{240}h^4$$

where  $h$  is the width of the class-interval while  $\mu_1$  and  $\mu_3$  require no correction.

These formulae are known as **Sheppard's corrections**.

**Example 3.** Find the corrected values of the following moments using Sheppard's correction. The width of classes in the distribution is 10:

$$\mu_2 = 214,$$

$$\mu_3 = 468,$$

$$\mu_4 = 96712.$$

**Sol.** We have  $\mu_2 = 214,$

$$\mu_3 = 468,$$

$$\mu_4 = 96712, \quad h = 10.$$

$$\text{Now, } \mu_2 (\text{corrected}) = \mu_2 - \frac{h^2}{12} = 214 - \frac{(10)^2}{12} = 214 - 8.333 = 205.667.$$

$$\mu_3 (\text{corrected}) = \mu_3 = 468$$

$$\begin{aligned}\mu_4 (\text{corrected}) &= \mu_4 - \frac{1}{2} h^2 \mu_2 + \frac{7}{240} h^4 = 96712 - \frac{(10)^2}{2} (214) + \frac{7}{240} (10)^4 \\ &= 96712 - 10700 - 291.667 = 86303.667.\end{aligned}$$

### 3.4 MOMENTS ABOUT AN ARBITRARY NUMBER (Raw Moments)

If  $x_1, x_2, x_3, \dots, x_n$  are the values of a variable  $x$  with the corresponding frequencies  $f_1, f_2, f_3, \dots, f_n$  respectively then  $r^{\text{th}}$  moment  $\mu_r'$  about the number  $x = A$  is defined as

$$\mu_r' = \frac{1}{N} \sum_{i=1}^n f_i (x_i - A)^r ; r = 0, 1, 2, \dots \quad \text{where, } N = \sum_{i=1}^n f_i$$

For  $r = 0$ , 
$$\mu_0' = \frac{1}{N} \sum_{i=1}^n f_i (x_i - A)^0 = 1$$

For  $r = 1$ , 
$$\mu_1' = \frac{1}{N} \sum_{i=1}^n f_i (x_i - A) = \frac{1}{N} \sum_{i=1}^n f_i x_i - \frac{A}{N} \sum_{i=1}^n f_i = \bar{x} - A$$

For  $r = 2$ , 
$$\mu_2' = \frac{1}{N} \sum_{i=1}^n f_i (x_i - A)^2$$

For  $r = 3$ , 
$$\mu_3' = \frac{1}{N} \sum_{i=1}^n f_i (x_i - A)^3 \text{ and so on.}$$

In calculation work, if we find that there is some common factor  $h (> 1)$  in values of  $x - A$ , we can ease our calculation work by defining  $u = \frac{x - A}{h}$ . In that case, we have

$$\mu_r' = \frac{1}{N} \left( \sum_{i=1}^n f_i u_i^r \right) h^r ; r = 0, 1, 2, \dots$$

**Note.** For an individual series,

$$1. \mu_r' = \frac{1}{n} \sum_{i=1}^n (x_i - A)^r ; r = 0, 1, 2, \dots$$

$$2. \mu_r' = \frac{1}{N} \left( \sum_{i=1}^n u_i^r \right) h^r ; r = 0, 1, 2, \dots$$

$$\left| \text{for } u = \frac{x - A}{h} \right|$$

### 3.5 MOMENTS ABOUT THE ORIGIN

If  $x_1, x_2, \dots, x_n$  be the values of a variable  $x$  with corresponding frequencies  $f_1, f_2, \dots, f_n$  respectively then  $r^{\text{th}}$  moment about the origin  $v_r$  is defined as

$$v_r = \frac{1}{N} \sum_{i=1}^n f_i x_i^r ; r = 0, 1, 2, \dots \quad \text{where, } N = \sum_{i=1}^n f_i$$



For  $r = 0$ , 
$$v_0 = \frac{1}{N} \sum_{i=1}^n f_i x_i^0 = \frac{N}{N} = 1$$

For  $r = 1$ , 
$$v_1 = \frac{1}{N} \sum_{i=1}^n f_i x_i = \bar{x}$$

For  $r = 2$ , 
$$v_2 = \frac{1}{N} \sum_{i=1}^n f_i x_i^2 \quad \text{and so on.}$$

### 3.6 RELATION BETWEEN $\mu_r$ AND $\mu'_r$

We know that,

$$\begin{aligned} \mu_r &= \frac{\sum_{i=1}^n f_i (x_i - \bar{x})^r}{N} = \frac{1}{N} \sum_{i=1}^n f_i [(x_i - A) - (\bar{x} - A)]^r \\ &= \frac{1}{N} \sum_{i=1}^n f_i [(x_i - A) - \mu'_1]^r \quad | \because \mu'_1 = \bar{x} - A \\ &= \frac{1}{N} \sum_{i=1}^n f_i [(x_i - A)^r - {}^r C_1 (x_i - A)^{r-1} \mu'_1 + {}^r C_2 (x_i - A)^{r-2} \mu_1'^2 - \dots + (-1)^r \mu_1'^r] \\ &\quad | \text{ Using binomial theorem} \end{aligned}$$

$$\Rightarrow \mu_r = \mu_r' - {}^r C_1 \mu_{r-1}' \mu_1' + {}^r C_2 \mu_{r-2}' \mu_1'^2 - \dots + (-1)^r \mu_1'^r$$

Putting  $r = 2, 3, 4$ , we get

$$\begin{aligned} \mu_2 &= \mu_2' - 2\mu_1'^2 + \mu_1'^2 = \mu_2' - \mu_1'^2 \quad | \because \mu_0' = 1 \\ \mu_3 &= \mu_3' - 3\mu_2' \mu_1' + 3\mu_1'^3 - \mu_1'^3 = \mu_3' - 3\mu_2' \mu_1' + 2\mu_1'^3 \\ \mu_4 &= \mu_4' - 4\mu_3' \mu_1' + 6\mu_2' \mu_1'^2 - 3\mu_1'^4 \end{aligned}$$

Hence, we have the following relations:

$$\mu_1 = 0$$

$$\mu_2 = \mu_2' - \mu_1'^2$$

$$\mu_3 = \mu_3' - 3\mu_2' \mu_1' + 2\mu_1'^3$$

and

$$\mu_4 = \mu_4' - 4\mu_3' \mu_1' + 6\mu_2' \mu_1'^2 - 3\mu_1'^4$$

### 3.7 RELATION BETWEEN $v_r$ AND $\mu_r$

We know that,

$$v_r = \frac{1}{N} \sum_{i=1}^n f_i x_i^r; \quad r = 0, 1, 2, \dots$$

$$\begin{aligned}
&= \frac{1}{N} \sum_{i=1}^n f_i (x_i - A + A)^r \\
&= \frac{1}{N} \sum_{i=1}^n f_i [(x_i - A)^r + {}^r c_1 (x_i - A)^{r-1} \cdot A + \dots + A^r] \\
&= \mu_r' + {}^r c_1 \mu_{r-1}' A + \dots + A^r
\end{aligned}$$

If we take,  $A = \bar{x}$  (for  $\mu_r$ ) then

$$v_r = \mu_r + {}^r c_1 \mu_{r-1} \bar{x} + {}^r c_2 \mu_{r-2} \bar{x}^2 + \dots + \bar{x}^r$$

Putting,  $r = 1, 2, 3, 4$  in (1), we get

...(1)

$$\begin{aligned}
v_1 &= \mu_1 + \mu_0 \bar{x} = \bar{x} \\
v_2 &= \mu_2 + {}^2 c_1 \mu_1 \bar{x} + {}^2 c_2 \mu_0 \bar{x}^2 = \mu_2 + \bar{x}^2 \quad | \quad \because \mu_1 = 0, \mu_0 = 1 \\
v_3 &= \mu_3 + {}^3 c_1 \mu_2 \bar{x} + {}^3 c_2 \mu_1 \bar{x}^2 + {}^3 c_3 \mu_0 \bar{x}^3 = \mu_3 + 3\mu_2 \bar{x} + \bar{x}^3 \\
v_4 &= \mu_4 + {}^4 c_1 \mu_3 \bar{x} + {}^4 c_2 \mu_2 \bar{x}^2 + {}^4 c_3 \mu_1 \bar{x}^3 + {}^4 c_4 \mu_0 \bar{x}^4 \\
&= \mu_4 + 4\mu_3 \bar{x} + 6\mu_2 \bar{x}^2 + \bar{x}^4
\end{aligned}$$

Hence we have the following relations:

$$v_1 = \bar{x}$$

$$v_2 = \mu_2 + \bar{x}^2$$

$$v_3 = \mu_3 + 3\mu_2 \bar{x} + \bar{x}^3$$

and

$$v_4 = \mu_4 + 4\mu_3 \bar{x} + 6\mu_2 \bar{x}^2 + \bar{x}^4$$

### 3.8 KARL PEARSON'S $\beta$ AND $\gamma$ COEFFICIENTS

Karl Pearson defined the following four coefficients based upon the first four moments of a frequency distribution about its mean:

$$\left. \begin{aligned} \beta_1 &= \frac{\mu_3}{\mu_2^{\frac{3}{2}}} \\ \beta_2 &= \frac{\mu_4}{\mu_2^2} \end{aligned} \right\} \quad (\beta\text{-coefficients})$$

$$\left. \begin{aligned} \gamma_1 &= +\sqrt{\beta_1} \\ \gamma_2 &= \beta_2 - 3 \end{aligned} \right\} \quad (\gamma\text{-coefficients})$$

The practical use of these coefficients is to measure the skewness and kurtosis of a frequency distribution. These coefficients are pure numbers independent of units of measurement.

#### EXAMPLES

**Example 1.** The first three moments of a distribution, about the value '2' of the variable are 1, 16 and -40. Show that the mean is 3, variance is 15 and  $\mu_3 = -86$ .

**Sol.** We have  $A = 2$ ,  $\mu_1' = 1$ ,  $\mu_2' = 16$ , and  $\mu_3' = -40$

We know that  $\mu_1' = \bar{x} - A \Rightarrow \bar{x} = \mu_1' + A = 1 + 2 = 3$

$$\text{Variance} = \mu_2 = \mu_2' - \mu_1'^2 = 16 - (1)^2 = 15$$

$$\mu_3 = \mu_3' - 3\mu_2'\mu_1' + 2\mu_1'^3 = -40 - 3(16)(1) + 2(1)^3 = -40 - 48 + 2 = -86.$$



**Example 2.** The first four moments of a distribution, about the value '35' are -1.8, 240, -1020 and 144000. Find the values of  $\mu_1, \mu_2, \mu_3, \mu_4$ .

**Sol.**

$$\mu_1 = 0.$$

$$\mu_2 = \mu_2' - \mu_1'^2 = 240 - (-1.8)^2 = 236.76$$

$$\mu_3 = \mu_3' - 3\mu_2'\mu_1' + 2\mu_1'^3 = -1020 - 3(240)(-1.8) + 2(-1.8)^3 = 264.36$$

$$\begin{aligned} \mu_4 &= \mu_4' - 4\mu_3'\mu_1' + 6\mu_2'\mu_1'^2 - 3\mu_1'^4 \\ &= 144000 - 4(-1020)(-1.8) + 6(240)(-1.8)^2 - 3(-1.8)^4 = 141290.11. \end{aligned}$$

**Example 3.** Calculate the variance and third central moment from the following data:

$x_i$	0	1	2	3	4	5	6	7	8
$f_i$	1	9	26	59	72	52	29	7	1

**Sol.**

### Calculation of Moments

(U.P.T.U. 2006)

$x$	$f$	$u = \frac{x-A}{h}$ $A = 4, h = 1$	$fu$	$fu^2$	$fu^3$
0	1	-4	-4	16	-64
1	9	-3	-27	81	-243
2	26	-2	-52	104	-208
3	59	-1	-59	59	-59
4	72	0	0	0	0
5	52	1	52	52	52
6	29	2	58	116	232
7	7	3	21	63	189
8	1	4	4	16	64
$N = \Sigma f = 256$			$\Sigma fu = -7$	$\Sigma fu^2 = 507$	$\Sigma fu^3 = -37$

Now, moments about the point  $x = A = 4$  are

$$\mu_1' = \left( \frac{\Sigma fu}{N} \right) h = \frac{-7}{256} = -0.02734$$

$$\mu_2' = \left( \frac{\Sigma fu^2}{N} \right) h^2 = \frac{507}{256} = 1.9805$$

$$\mu_3' = \left( \frac{\Sigma fu^3}{N} \right) h^3 = \frac{-37}{256} = -0.1445$$

### Moments about mean

$$\mu_1 = 0$$

$$\mu_2 = \mu_2' - \mu_1'^2 = 1.9805 - (-0.02734)^2 = 1.97975$$

$$\therefore \text{Variance} = 1.97975$$

Also,

$$\mu_3 = \mu_3' - 3\mu_2'\mu_1' + 2\mu_1'^3$$

## STATISTICAL TECHNIQUES

---

$$\begin{aligned} &= (-0.1445) - 3(1.9805)(-0.02734) + 2(-0.02734)^3 \\ &= 0.0178997 \end{aligned}$$

$\therefore$  Third central moment = 0.0178997.

**Example 4.** The first three moments of a distribution about the value 2 of the variate are 1, 16 and -40 respectively. Find the values of the first three moments about the origin.

**Sol.** We have

$$A = 2, \quad \mu'_1 = 1, \quad \mu'_2 = 16, \quad \mu'_3 = -40$$

$\therefore$

$$v_1 = \bar{x} = A + \mu'_1 = 2 + 1 = 3$$

$$v_2 = \mu_2 + \bar{x}^2 = 15 + (3)^2 = 24$$

$$v_3 = \mu_3 + 3\mu_2\bar{x} + \bar{x}^3 = -86 + 3(15)(3) + (3)^3 = 76.$$



For certain theoretical developments, an indirect method for computing moments is used. This method depends on the finding of the moment generating function.

**3.9.1. In Case of a Continuous Variable  $x$ ,** it is defined as

$$M(t) = \int_a^b e^{tx} f(x) dx \quad \dots(1)$$

where integral is a function of parameter  $t$  only. The limits  $a, b$  can be  $-\infty$  and  $\infty$  respectively. It is possible to associate a moment generating function with the distribution only when all the moments of the distribution are finite.

Let us see how  $M(t)$  generates moments. For this, let us assume that  $f(x)$  is a distribution function for which the integral given by (1) exists.

Then  $e^{tx}$  may be expanded in a power series and the integration may be performed term by term. It follows that

$$\begin{aligned} M(t) &= \int_a^b \left( 1 + tx + \frac{t^2}{2!} x^2 + \dots \right) f(x) dx \\ &= \int_a^b f(x) dx + t \int_a^b x f(x) dx + \dots \end{aligned}$$

$$= v_0 + v_1 t + v_2 \cdot \frac{t^2}{2!} + \dots \quad \dots(2)$$

Obviously, the coefficient of  $\frac{t^r}{r!}$  in (2) is the  $r^{\text{th}}$  moment about the origin.

$$\text{Also, } \left| \frac{d^r}{dt^r} M(t) \right|_{t=0} = \left| \frac{v_r}{r!} r! + v_{r+1} t + \dots \right|_{t=0} = v_r \quad \dots(3)$$

Thus,  $v_r$  about origin =  $r^{\text{th}}$  derivative of  $M(t)$  with  $t = 0$ .

Although the moment generating function (m.g.f.) has been defined for the variable  $x$  only, the definition can be generalized so that it holds for a variable  $z$  where  $z$  is a function of  $x$ . e.g., if  $z = x - m$  ( $m$  is mean), the  $r^{\text{th}}$  moment about  $z$  will give  $r^{\text{th}}$  moment of  $x$  about the mean  $m$ .

Moment generating function for  $z$  will clearly be given as

$$M_z(t) = \int_a^b e^{tz} f(x) dx$$

$$M_{x-m}(t) = \int_a^b e^{t(x-m)} f(x) dx = e^{-mt} \int_a^b e^{tx} f(x) dx = e^{-mt} M_x(t).$$

### 3.9.2. In Case of Discrete Distribution of the Variable $x$

We know that, for a variable  $x$ ,

$$v_r = \sum x^r \cdot P$$

where  $P$  is the probability that the variable takes on the value  $x$ .

If  $z$  is any function of  $x$ , we get  $r^{\text{th}}$  moment for  $z$  by the relation

$$v_r = \sum z^r P$$

and the moment generating function is given by

$$M_z(t) = \sum e^{tz} P \quad \dots(1)$$

To verify that this function generates moments, we will expand  $e^{tz}$  and then sum term by term,

$$\therefore M_z(t) = \sum \left( 1 + tz + \frac{t^2}{2!} z^2 + \dots \right) P = \sum P + t \sum zP + \frac{t^2}{2!} \sum z^2 \cdot P + \dots$$

$$= v_0 + tv_1 + \frac{t^2}{2!} v_2 + \dots$$

$$\text{In this case, we can also show that } v_r = \left| \frac{d^r}{dt^r} M_z(t) \right|_{t=0}$$

$M(t)$  is clearly the expected value of  $e^{tx}$  and hence can be written as  $E(e^{tx})$  which gives the moment generating function in case of discrete as well as continuous variables.

Expectation of any function  $\phi(x)$  is given by

$$E\{\phi(x)\} = \sum_i \phi(x_i) f(x_i) \quad | \text{ for discrete distribution}$$

$$\text{or, } E\{\phi(x)\} = \int_{-\infty}^{\infty} \phi(x) f(x) dx \quad | \text{ for continuous distribution}$$



Eqn. (1) can also be rewritten as

$$M_{x-a}(t) = E[e^{t(x-a)}] = \sum_i e^{t(x_i-a)} P_i = e^{-at} \sum_i e^{tx_i} P_i = e^{-at} M_0(t)$$

Therefore the moment generating function about the point 'a' is equal to  $e^{-at}$  times the moment generating function about the origin.

**Note.** m.g.f. is not always defined since  $E[|e^{tx}|]$  does not always exist for all values of  $t$ .

e.g., if  $f(x) = \frac{6}{\pi^2 x^2}$ ,  $x = 1, 2, 3, \dots$  then m.g.f. does not exist.

m.g.f. always exists for  $t = 0$  since  $M_{x=0}(0) = 1$ .

(M.T.U. 2013)

### 3.9.3. Properties of Moment Generating Function

(1) The moment generating function of the sum of two independent chance variables is the product of their respective moment generating functions.

Symbolically,  $M_{x+y}(t) = M_x(t) \times M_y(t)$  provided that  $x$  and  $y$  are independent random variables.

**Proof.** Let  $x$  and  $y$  be two independent random variables so that  $x + y$  is also a random variable.

The m.g.f. of the sum  $x + y$  w.r.t. origin is

$$M_{x+y}(t) = E[e^{t(x+y)}] = E(e^{tx} \cdot e^{ty}) = E(e^{tx}) \cdot E(e^{ty})$$

Since  $x$  and  $y$  are independent variables and so are  $e^{tx}$  and  $e^{ty}$ .

$$\therefore M_{x+y}(t) = M_x(t) \cdot M_y(t)$$

Hence the theorem.

(2) Effect of change of origin and scale on m.g.f.

$$M_u(t) = e^{-at/h} M_x(t/h)$$

$$\text{where } u = \frac{x-a}{h}$$

**Proof.** Let  $u$  be a new random variable given by  $u = \frac{x-a}{h}$  so that  $x = a + hu$

then by definition, the effect of linear transformation on m.g.f. is governed by

$$\begin{aligned} M_x(t) &= E(e^{tx}) = E[e^{t(a+hu)}] = E(e^{at} \cdot e^{thu}) \\ &= e^{at} E(e^{thu}) = e^{at} M_u(th) \end{aligned}$$

Also,

$$M_u(t) = E(e^{tu})$$

$$= E\left[e^{t\left(\frac{x-a}{h}\right)}\right] = e^{-\frac{at}{h}} M_x\left(\frac{t}{h}\right)$$

(3)

$$M_{cx}(t) = M_x(ct), \text{ } c \text{ being a constant.}$$

**Proof.** By definition,

$$\text{LHS} = M_{cx}(t) = E(e^{tcx}) = M_x(ct) = \text{RHS}$$

Hence the result.

## EXAMPLES

**Example 1.** Find the moment generating function of the exponential distribution

$$f(x) = \frac{1}{c} e^{-x/c}; 0 \leq x \leq \infty, c > 0$$

Hence find its mean and standard deviation.

**Sol.** Moment generating function about the origin is given by

$$\begin{aligned} M_x(t) &= \int_0^{\infty} e^{tx} \cdot \frac{1}{c} e^{-x/c} dx \\ &= \frac{1}{c} \int_0^{\infty} e^{\left(t - \frac{1}{c}\right)x} dx = \frac{1}{c} \left[ \frac{e^{\left(t - \frac{1}{c}\right)x}}{\left(t - \frac{1}{c}\right)} \right]_0^{\infty} \\ &= (1 - ct)^{-1} = 1 + ct + c^2 t^2 + c^3 t^3 + \dots \end{aligned}$$

$$\therefore v_1 = \left[ \frac{d}{dt} M_x(t) \right]_{t=0} = (c + 2c^2 t + 3c^3 t^2 + \dots)_{t=0} = c$$

$$v_2 = \left[ \frac{d^2}{dt^2} M_x(t) \right]_{t=0} = 2c^2$$

and

Now, mean

Variance

$$\bar{x} = v_1 = c$$

$$\mu_2 = v_2 - \bar{x}^2 = v_2 - v_1^2 = 2c^2 - c^2 = c^2$$

$$\therefore \text{Standard deviation} = \sqrt{\mu_2} = c.$$

**Example 2.** Obtain the moment generating function of the random variable  $x$  having probability distribution

$$f(x) = \begin{cases} x, & \text{for } 0 < x < 1 \\ 2 - x, & \text{for } 1 \leq x < 2 \\ 0, & \text{elsewhere} \end{cases}$$

Also determine mean  $v_1$ ,  $v_2$  and variance  $\mu_2$ .

**Sol.**  $M_x(t) = E(e^{tx})$

$$\begin{aligned} &= \int_0^1 x \cdot e^{tx} dx + \int_1^2 (2 - x) e^{tx} dx + \int_2^{\infty} 0 \cdot e^{tx} dx \\ &= \left( \frac{x e^{tx}}{t} - \frac{e^{tx}}{t^2} \right)_0^1 + \left( \frac{2e^{tx}}{t} - \frac{x e^{tx}}{t} + \frac{e^{tx}}{t^2} \right)_1^2 \\ &= \frac{e^t}{t} - \frac{e^t}{t^2} + \frac{1}{t^2} + \left[ \left( \frac{2e^{2t}}{t} - \frac{2e^{2t}}{t} + \frac{e^{2t}}{t^2} \right) - \left( \frac{2e^t}{t} - \frac{e^t}{t} + \frac{e^t}{t^2} \right) \right] = \frac{e^{2t} - 2e^t + 1}{t^2} \\ &= \left( \frac{e^t - 1}{t} \right)^2 = \frac{\left( t + \frac{t^2}{2!} + \frac{t^3}{3!} + \dots \right)^2}{t^2} = 1 + t + t^2 + \dots \end{aligned}$$



$$\text{Mean} = v_1 = \left[ \frac{d}{dt} M_x(t) \right]_{t=0} = 1$$

Similarly,  $v_2 = 2$ ,  $\mu_2 = v_2 - \bar{x}^2 = v_2 - v_1^2 = 2 - (1)^2 = 1 = \text{Variance}$ .

**Example 3.** Find the moment generating function of the random variable whose moments are  $v_r = (r+1)! 2^r$ .

**Sol.**

$$\begin{aligned} M_x(t) &= E(e^{tx}) = \sum_{x=0}^{\infty} e^{tx} P(X=x) \\ &= \sum_{r=0}^{\infty} \frac{t^r}{r!} v_r = \sum_{r=0}^{\infty} \frac{t^r}{r!} (r+1)! 2^r = \sum_{r=0}^{\infty} (r+1) (2t)^r \\ &= 1 + 2 \cdot 2t + 3 \cdot (2t)^2 + \dots = (1 - 2t)^{-2}. \end{aligned}$$

**Example 4.** Find the moment generating function of the probability distribution function

$$f(z) = e^{-z} (1 + e^{-z})^{-2}, \quad -\infty < z < \infty.$$

**Sol.**

$$M_z(t) = E(e^{tz})$$

$$= \int_{-\infty}^{\infty} e^{tz} \cdot e^{-z} (1 + e^{-z})^{-2} dz$$

$$= \int_1^{\infty} u^2 (u-1)^{-t} du \quad \text{where } 1 + e^{-z} = u \Rightarrow -e^{-z} dz = du$$

$$= \int_0^1 v^{-t} (1-v)^t dv \quad \text{where } v = 1 - \frac{1}{u} \Rightarrow dv = \frac{1}{u^2} du$$

$$= \beta(1-t, 1+t); \quad 1-t > 0$$

$$= \pi t \operatorname{cosec} \pi t, \quad t < 1.$$

**Example 9.** The random variable  $X$  assuming only non-negative values has a Gamma probability distribution if its probability distribution is given by

$$f(x) = \begin{cases} \frac{\alpha^\beta}{\Gamma\beta} x^{\beta-1} e^{-\alpha x} & ; x > 0, \alpha > 0, \beta > 1 \\ 0, & \text{elsewhere} \end{cases}$$

Find the moment generating function of Gamma probability distribution.

**Sol.**

$$M_x(t) = E(e^{tx})$$

$$= \int_0^\infty e^{tx} \cdot \frac{\alpha^\beta}{\Gamma\beta} \cdot x^{\beta-1} e^{-\alpha x} dx = \frac{\alpha^\beta}{\Gamma\beta} \int_0^\infty x^{\beta-1} e^{-x(\alpha-t)} dx$$

$$= \frac{\alpha^\beta}{(\alpha-t)^\beta \Gamma\beta} \int_0^\infty y^{\beta-1} e^{-y} dy \quad | \text{ where } y = x(\alpha-t) \text{ so that } dy = (\alpha-t) dx$$

$$= \frac{1}{\left(1 - \frac{t}{\alpha}\right)^\beta} \cdot \frac{1}{\Gamma\beta} \Gamma\beta = \left(1 - \frac{t}{\alpha}\right)^{-\beta} ; |t| < \alpha.$$