

Mathematical Expectation and Moment Generating Function

MATHEMATICAL EXPECTATION

The expected value of the random variable X or the expectation of the random variable X , denoted by $E(X)$ is defined by

$$E(X) = \begin{cases} \int x f_X(x) dx, & \text{if } x \text{ is a cont. r.v.,} \\ \sum x p(x), & \text{if } x \text{ is a disc. r.v..} \end{cases}$$

Ex. What is expected value of the number of points obtained in a single throw with an ordinary dice?

Sol. Here the random variable X is the number of points of the dice which assumes the values 1,2,3,4,5,6 each with a probability $\frac{1}{6}$

$X = x$	0	1	2	3	4	5	6
$P(X = x)$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$

$$\begin{aligned} E(X) &= \sum x p(x) = 1 \times \frac{1}{6} + 2 \times \frac{1}{6} + 3 \times \frac{1}{6} + 4 \times \frac{1}{6} + 5 \times \frac{1}{6} + 6 \times \frac{1}{6} \\ &= (1 + 2 + 3 + 4 + 5 + 6) \times \frac{1}{6} = \frac{21}{6} \end{aligned}$$

Ex. Suppose the random variable X takes the values 0,1,2,...with probability mass function

$$p(x) = \frac{e^{-\lambda} \lambda^x}{x!}$$

Sol. We know that $E(X) = \sum_{x=0}^{\infty} x p(x) = \sum_{x=0}^{\infty} x \frac{e^{-\lambda} \lambda^x}{x!}$

$$= \lambda e^{-\lambda} \sum_{x=1}^{\infty} \frac{\lambda^{(x-1)}}{(x-1)!} = \lambda e^{-\lambda} e^{\lambda} = \lambda$$

Ex. Suppose the random variable X with probability density function $f(x) = \lambda e^{-\lambda x}$, $x > 0$

Sol. We know that $E(X) = \int_0^{\infty} x f(x) dx = \int_0^{\infty} x \lambda e^{-\lambda x} dx =$

$$= \lambda \int_0^{\infty} x e^{-\lambda x} dx = \lambda \int_0^{\infty} x^{(2-1)} e^{-\lambda x} dx = \frac{\lambda}{\lambda^2} = \frac{1}{\lambda}$$

Th. If a and b are constants, then $E(aX + b) = aE(X) + b$

Prof. $E(X) = \sum (ax + b)p(x) = a \sum xp(x) + b \sum p(x) = aE(X) + b.$

Th. The expectation of the sum of two random variable X and Y is equal to the sum of their expectation.

$$E(X + Y) = E(X) + E(Y).$$

Prof. $E(X + Y) = \int \int (x + y)f(x, y)dx dy$
 $= \int \int x f(x, y)dx dy + \int \int y f(x, y)dx dy$
 $= \int x \int f(x, y)dy dx + \int y \int f(x, y)dx dy$
 $= \int x g(x) dx + \int y h(y) dy = E(X) + E(Y)$
 so, $E(X + Y) = E(X) + E(Y).$

Th. If X and Y be two independent random variable, then

$$E(XY) = E(X)E(Y).$$

Prof. Since X and Y be two independent random variable, then $f(x, y) = f(x)f(y)$

$E(XY) = \int \int xy f(x, y)dx dy = \int \int xy f(x) f(y)dx dy$
 $= \int x f(x)dx \int y f(y)dy = E(X)E(Y).$
 so $E(XY) = E(X)E(Y).$

Expectation of a Linear Combination of Random Variables : Suppose Y_1, Y_2, \dots, Y_m be any m random variables and if b_1, b_2, \dots, b_m are any m constants, then

$$E\left(\sum_{j=1}^m b_j Y_j\right) = \sum_{j=1}^m b_j E(Y_j)$$

MATHEMATICAL EXPECTATION of a Function of a Random Variable

The expected value of a function of a random variable denoted by $E(h(X))$ is defined by

$$E(h(X)) = \begin{cases} \int h(x) f_X(x)dx, & \text{if } h(x) \text{ is a cont. r.v.,} \\ \sum h(x)p(x), & \text{if } h(x) \text{ is a disc. r.v..} \end{cases}$$

VARIANCE

The variance of the random variable X or the variance of the random variable X , denoted by $V(X)$ is defined by

$$V(X) = \mu_2 = E(x - \bar{x})^2 = \begin{cases} \int (x - \bar{x})^2 f_X(x) dx, & \text{if } x \text{ is a cont. r.v.}, \\ \sum (x - \bar{x})^2 p(x), & \text{if } x \text{ is a disc. r.v.} \end{cases}$$

where, $\bar{x} = \mu = E(X)$

Th. $V(X) = E(X^2) - (E(X))^2$

Prof. $V(X) = E(X - \bar{X})^2 = E(X^2 + \bar{X}^2 - 2\bar{X}X)$

$$= E(X^2) + \bar{X}^2 - 2\bar{X}E(X) = E(X^2) + \bar{X}^2 - 2\bar{X}\bar{X} = E(X^2) - \bar{X}^2$$

So, $V(X) = E(X^2) - (E(X))^2$

Th. $V(aX + b) = a^2 V(X)$

Prof. $Y = aX + b$ then $E(Y) = aE(X) + b$

$$\Rightarrow Y - E(Y) = a(X - E(X)),$$

Squaring and taking expectation of both sides, we get

$$E(Y - E(Y))^2 = a^2 E(X - E(X))^2 \Rightarrow V(Y) = a^2 V(X)$$

$$\Rightarrow V(aX + b) = a^2 V(X)$$

Th. $V(X + Y) = V(X) + V(Y) + 2Cov(X, Y)$

Prof. $E(X + Y) = E(X) + E(Y)$ then

$$\Rightarrow V(X + Y) = E[(X + Y) - E(X + Y)]^2$$

$$\Rightarrow E[(X + Y) - E(X) - E(Y)]^2$$

$$\Rightarrow E[(X - E(X)) + (Y - E(Y))]^2$$

$$\Rightarrow E[(X - E(X))^2 + (Y - E(Y))^2 + 2(X - E(X))(Y - E(Y))]$$

$$\begin{aligned} &\Rightarrow E(X - E(X))^2 + E(Y - E(Y))^2 + 2E((X - E(X))(Y - E(Y))) \\ &= V(X) + V(Y) + 2Cov(X, Y) \end{aligned}$$

So, $V(X + Y) = V(X) + V(Y) + 2Cov(X, Y)$

Th. $Cov(X, Y) = E(XY) - E(X)E(Y)$

Prof. $Cov(X, Y) = E\{(X - E(X))(Y - E(Y))\}$

$$\Rightarrow E\{XY - XE(Y) - YE(X) + E(X)E(Y)\},$$

$$\Rightarrow E(XY) - E(X)E(Y) - E(Y)E(X) + E(X)E(Y),$$

$$\Rightarrow E(XY) - E(X)E(Y),$$

So, $Cov(X, Y) = E(XY) - E(X)E(Y)$

If X and Y are two independent variates the $E(XY) = E(X)E(Y)$

$$\Rightarrow Cov(X, Y) = E(XY) - E(X)E(Y),$$

$$\Rightarrow Cov(X, Y) = E(X)E(Y) - E(X)E(Y) \Rightarrow Cov(X, Y) = 0.$$

So we can say that if X and Y are two independent variates then $Cov(X, Y) = 0$

Moment Generating Function

The Moment generating function of the random variable X denoted by $M_X(t)$ is defined by

$$M_X(t) = E(e^{tX}) = \begin{cases} \int e^{tx} f_X(x) dx, & \text{if } x \text{ is a cont. r.v.,} \\ \sum e^{tx} p(x), & \text{if } x \text{ is a disc. r.v..} \end{cases}$$

$$M_X(t) = E(e^{tX}) = \sum e^{tx} p(x)$$

The series expansion for e^{tx}

$$e^{tx} = 1 + tx + \frac{(tx)^2}{2!} + \frac{(tx)^3}{3!} + \dots + \frac{(tx)^r}{r!} + \dots$$

$$M_X(t) = \sum \left[1 + tx + \frac{(tx)^2}{2!} + \frac{(tx)^3}{3!} + \dots + \frac{(tx)^r}{r!} + \dots \right] p(x)$$

$$\begin{aligned} &\Rightarrow \sum p(x) + t \sum x p(x) + \frac{t^2}{2!} \sum x^2 p(x) + \frac{t^3}{3!} \sum x^3 p(x) + \dots + \frac{t^r}{r!} \sum x^r p(x) \\ &\Rightarrow 1 + \mu'_1 t + \mu'_2 \frac{t^2}{2!} + \mu'_3 \frac{t^3}{3!} + \dots + \mu'_r \frac{t^r}{r!} + \dots \end{aligned}$$

where,

$$\mu'_r = E(X^r) = \sum x^r p(x) \text{ is the } r^{\text{th}} \text{ moment of } X \text{ about origin.}$$

Hence, we see that the co-efficient of $\frac{t^r}{r!}$ in $M_X(t)$ gives μ'_r

A simplified procedure of obtaining the few moment is using the following formula

$$\mu'_r = \left. \frac{d^r M_X(t)}{dt^r} \right|_{t=0}$$

Th. $M_{aX+b}(t) = e^{bt} M_X(at)$

Prof. $M_{aX+b}(t) = E[e^{t(aX+b)}] = E[e^{t(aX)} e^{bt}] = e^{bt} E[e^{t(aX)}]$

$$\Rightarrow e^{bt} E[e^{at(X)}] = e^{bt} M_X(at)$$

Th. If X_1, X_2, \dots, X_n are independent random variable, then the moment generating function of their sum $(X_1 + X_2 + \dots + X_n)$ is given by $M_{(X_1+X_2+\dots+X_n)}(t) = M_{X_1}(t) M_{X_2}(t) \dots M_{X_n}(t)$

Prof. $M_{(X_1+X_2+\dots+X_n)}(t) = E(e^{t(X_1+X_2+\dots+X_n)}) = E(e^{tX_1} e^{tX_2} \dots e^{tX_n})$

$$\Rightarrow E(e^{tX_1}) E(e^{tX_2}) \dots E(e^{tX_n}) \quad (\because X_1, X_2, \dots, X_n \text{ are independent})$$

$$M_{(X_1+X_2+\dots+X_n)}(t) = M_{X_1}(t) M_{X_2}(t) \dots M_{X_n}(t)$$

Ex. Let the random variable X assume the value x with the probability law: $P(X = x) = pq^{(x-1)}$; $x = 1, 2, 3, 4, \dots$ and $p + q = 1$. Find the m.g.f. and hence the Mean and Variance.

Sol. $M_X(t) = E(e^{tX}) = \sum e^{tx} P(X = x) = \sum e^{tx} pq^{(x-1)}$

$$\Rightarrow \frac{p}{q} \sum (qe^{t})^x = \frac{p}{q} [qe^t + (qe^t)^2 + \dots]$$

$$\Rightarrow \frac{p}{q} qe^t [1 + qe^t + (qe^t)^2 + \dots] = \frac{pe^t}{1 - qe^t}$$

$$\text{So, } M_X(t) = \frac{pe^t}{1 - qe^t} \text{ and } \mu'_r = \left. \frac{d^r M_X(t)}{dt^r} \right|_{t=0}$$

$$\text{We obtain } \mu'_1 = \left. \frac{dM_X(t)}{dt} \right|_{t=0}$$

$$\mu'_1 = \frac{p e^t}{(1 - q e^t)^2} \Big|_{t=0} = \frac{p}{(1 - q)^2} = \frac{1}{p}, \quad \text{so Mean} = \frac{1}{p}$$

$$\mu'_2 = \frac{p e^t (1 + q e^t)}{(1 - q e^t)^3} \Big|_{t=0} = \frac{p(1 + q)}{(1 - q)^3} = \frac{(1 + q)}{p^2}$$

$$\text{so Variance } \mu_2 = \mu'_2 - (\mu'_1)^2 = \frac{(1 + q)}{p^2} - \frac{1}{p^2} = \frac{q}{p^2}$$

Ex. Find the m.g.f of the random variable X having the probability density function

$$f(x) = \begin{cases} x & 0 \leq x \leq 1 \\ 2 - x & 1 \leq x \leq 2 \\ 0 & \text{otherwise.} \end{cases}$$

$$\text{Sol. } M_X(t) = E(e^{tX}) = \int e^{tx} f(x) dx$$

$$\Rightarrow \int_0^1 x e^{tx} dx + \int_1^2 (2 - x) e^{tx} dx = \frac{e^{2t}}{t^2} - \frac{2e^t}{t^2} + \frac{1}{t^2}$$

$$\Rightarrow \frac{1}{t^2} [1 + e^{2t} - 2e^t]$$

Now expanding $M_X(t)$, we have

$$\Rightarrow \frac{1}{t^2} \left[1 + \left(1 + 2t + \frac{(2t)^2}{2!} + \frac{(2t)^3}{3!} + \dots \right) - 2 \left(1 + t + \frac{t^3}{3!} + \dots \right) \right]$$

$$\Rightarrow \frac{1}{t^2} [t^2 + t^3 + \frac{7}{12} t^4 + \dots] = 1 + t + \frac{7}{12} t^2 + \dots$$

$$\mu'_1 = \text{Coefficient of } t \text{ in } M_X(t) = 1,$$

$$\mu'_2 = \text{Coefficient of } \frac{t^2}{2!} \text{ in } M_X(t) = 2! \frac{7}{12} = \frac{7}{6},$$

$$\text{so Variance } \mu_2 = \mu'_2 - (\mu'_1)^2 = \frac{7}{6} - 1 = \frac{1}{6}$$

Assignment

1. Find the m.g.f. of the discrete random variable X that has the probability distribution $P(X = x) = 2 \left(\frac{1}{3}\right)^x$; $x = 1, 2, 3, \dots$ and use it to determine the Mean and Variance.

2. Show that if a random variable has the probability density

$$f(x, y) = \begin{cases} \frac{1}{2} e^x & -\infty < x < 0 \\ \frac{1}{2} e^{-x} & 0 < x < \infty. \end{cases}$$

its M.G.F. is given by $M_X(t) = \frac{1}{1-t^2}$ and hence the Mean and Variance.

3. Compute the m.g.f. of the distribution defined by $f(x) = x e^{-x}$; $x > 0$ and use it to determine the Mean and Variance.

4. Find M.G.F., mean and variance for the p.d.f. $f(x) = c e^{-x}$; $x > 0$ where c is an unknown constant. Find c also.

5. Find the m.g.f. of the discrete random variable X that has the probability distribution $P(X = x) = \frac{\lambda^x e^{-\lambda}}{x!}$; $x = 0, 1, 2, 3, \dots$ and use it to determine the Mean and Variance.

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