

increasing or decreasing for all values within the range of x which $f(x) \neq 0$, then the probability density function of Y is given by

$$h(y) = f(x) \cdot \left| \frac{dx}{dy} \right|, \quad \frac{dy}{dx} \neq 0 \quad \dots (6.5.1)$$

For example, if X is uniformly distributed over $(0,2)$ and if $Y = e^X$, then $x = \ln y$,

$$\frac{dx}{dy} = \frac{1}{y}, \quad y \neq 0$$

$$\text{We have } f(x) = \begin{cases} \frac{1}{2}, & 0 < x < 2 \\ 0 & \text{otherwise} \end{cases}$$

Therefore, by (6.5.1) the density function of Y is

$h(y) = \frac{1}{2} \cdot \frac{1}{y}$ for $1 < y < e^2$, and the range of y is obtained as follows

For $x=0$, $y=e^0 = 1$ and for $x=2$, $y=e^2$.

Hence we can find the expectation of Y as follows

$$E(Y) = \int_1^{e^2} y \cdot \frac{1}{2y} dy = \left. \frac{1}{2} y \right]_1^{e^2} = \frac{e^2 - 1}{2}$$

Proposition 6.5.1.

1. If X is a discrete r.v. with p.m.f. $P(x)$, then for any real-valued function $Y = g(X)$,

$$E(Y) = E(g(X)) = \sum_x g(x) P(x) \quad \dots (6.5.2)$$

2. If X is a continuous r.v. with p.d.f. $f(x)$, then for any real-valued function $Y = g(X)$,

$$E(Y) = E[g(X)] = \int_{-\infty}^{\infty} g(x) f(x) dx \quad \dots (6.5.3)$$

Example 6.5.1.

If a r. v. X has the geometric distribution

$$P(x) = p(1-p)^{x-1}, x = 1, 2, \dots$$

and the values of the r.v. Y are related to those of X by means of the equation $y = 3 - 2x$, then the probability distribution of Y is

$$h(y) = f(x),$$

$$\text{where } x = \frac{3-y}{2}$$

$$\text{hence } h(y) = p(1-p)^{\frac{3-y}{2}-1} = p(1-p)^{\frac{1-y}{2}} \text{ for } y = 1, -1, -3, -5, \dots$$

Thus, by applying (6.5.2), we get

$$\begin{aligned} E(Y) &= \sum g(x) P(x) \\ &= \sum_{x=1}^{\infty} (3 - 2x) p(1-p)^{x-1} \\ &= 3 \sum_{x=1}^{\infty} p(1-p)^{x-1} - 2 \sum_{x=1}^{\infty} x p(1-p)^{x-1} \\ &= 3 - 2/p \end{aligned}$$

This result can also be obtained if we apply the formula

$$E(Y) = \sum y h(y) \quad \text{for } y = 1, -1, -3, -5, \dots$$

$$= \sum y p(1-p)^{\frac{1-y}{2}}$$

$$p + (-1)pq + (-3)pq^2 + (-5)pq^3 + \dots$$

$$= p - pq [1 + 3q + 5q^2 + 7q^3 + \dots]$$

$$= p - pq \left[\sum_{n=0}^{\infty} (2n+1)q^n \right]$$

$$= p - pq \left[2 \sum_{n=0}^{\infty} nq^n + \sum_{n=0}^{\infty} q^n \right]$$

$$= p - 2pq^2 \sum_{n=0}^{\infty} nq^{n-1} - pq \sum_{n=0}^{\infty} q^n$$

$$= p - 2pq^2 \cdot \frac{1}{(1-q)^2} - \frac{pq}{1-q}$$

$$= p - \frac{2q^2}{p} + q$$

$$= (2p - q) - \frac{2(1-p)^2}{p}$$

$$= 3 - 2/p.$$

Example 6.5.2.

Given the r.v. X with p.d.f.

$$f(x) = \begin{cases} \frac{1}{2}x, & 0 < x < 2 \\ 0, & \text{otherwise} \end{cases}$$

Find the p.d.f. of Y , whose values are related to those of X by means of the equation $y = x^2$.

Solution:

Since $y = x^2$, then $\frac{dy}{dx} = 2x$,

or $\frac{dx}{dy} = \frac{1}{2x} = \frac{1}{2\sqrt{y}}$, $y \neq 0$

$x = \sqrt{y}$

$\frac{dx}{dy} = \frac{1}{2\sqrt{y}}$

Since $0 < x < 2$, then we neglect the negative sign. By applying (6.5.1), we get

$h(y) = f(x) \cdot \left| \frac{dx}{dy} \right|$

$= f(\sqrt{y}) \cdot \left| \frac{1}{2\sqrt{y}} \right|$

$= \frac{\sqrt{y}}{2} \cdot \frac{1}{2\sqrt{y}} = \frac{1}{4}$, $0 < y < 4$

$x = \sqrt{y}$

$\frac{dx}{dy} = \frac{1}{2\sqrt{y}}$

Therefore, the r.v. Y has a uniform distribution over (0,4).

To find the expected value of Y , we have

$E(Y) = \int_0^4 y h(y) dy$

$= \int_0^4 \frac{y}{4} dy = \left[\frac{y^2}{8} \right]_0^4 = \frac{16}{8} = 2$

The same result can be obtained if we apply (6.5.3) as

$E(Y) = \int_{-\infty}^{\infty} g(x) f(x) dx$

$= \int_0^2 x^2 \cdot \frac{1}{2} dx = \left[\frac{x^3}{6} \right]_0^2 = \frac{8}{6} = \frac{4}{3}$

Theorem 6.5.1.

Let X be a r.v. , then for any constants a and b , we have
 $E(aX + b) = a E(X) + b$

Proof.

We prove this theorem for a continuous case. Let X be a continuous r.v. with p.d.f. f , then by Proposition (6.5.1.) we get

$$\begin{aligned} E(aX + b) &= \int_{-\infty}^{\infty} (ax + b)f(x) dx \\ &= a \int_{-\infty}^{\infty} xf(x) dx + b \int_{-\infty}^{\infty} f(x) dx \\ &= a E(X) + b \cdot 1 \\ &= a E(X) + b \end{aligned}$$

Theorem 6.5.2.

Let X be a r.v. and for any constants a and b , we have

i. $E[ag(X) + b] = a E[g(x)] + b.$

ii. $E(a) = a.$

where $g(X)$ is any function of X

Proof.

We prove this theorem for a discrete case.
Assume that X can take values x_1, x_2, \dots, x_n with respective probabilities $P(x_1), P(x_2), \dots, P(x_n)$ then by Proposition (6.5.1), we have

$$\begin{aligned} \text{i. } E[ag(X) + b] &= \sum_{i=1}^n [ag(x_i) + b] \cdot P(x_i) \\ &= a \sum_{i=1}^n g(x_i) P(x_i) + b \sum_{i=1}^n P(x_i) \end{aligned}$$

$$= aE [g (X)] + b \cdot 1$$

$$= a E [g (X)] + b$$

ii. If $g (X) = 1$ and $b=0$, then $E (a) = a$.

6.6. Variance and Other Moments

Definition 6.6.1.

The *variance* of a r.v. X is denoted by $\text{Var} (X)$ or σ_x^2 and is defined by

$$\text{Var} (X) = E [X - E (X)]^2 \quad \dots\dots\dots (6.6.1)$$

where $E (X)$ is the expectation of X .

Equation (6.6.1.) can be written as

$$\text{Var} (X) = E (X^2) - [E (X)]^2$$

where

$$\begin{aligned} E (X^2) &= \int_{-\infty}^{\infty} x^2 f (x) dx \text{ if } X \text{ is a continuous} \\ &= \sum_x x^2 P (x) \text{ if } X \text{ is a discrete r. v.} \end{aligned}$$

Definition 6.6.2.

The *r- th moment* about the origin is denoted by m_r , if it exists it is defined by

$$m_r = E (X^r), r = 1, 2, 3, \dots$$

i. e.

$$m_r = \sum_x x^r P (x) \text{ if } X \text{ is discrete}$$

$$= \int_{-\infty}^{\infty} x^r f (x) dx \text{ if } X \text{ is continuous} \quad \dots (6.6.2)$$

The r -th central moment about the mean $m = E(X)$, is denoted by μ_r , if it exists it is defined by

$$\mu_r = E[X - m]^r, r = 1, 2, 3, \dots$$

i. e.

$$\begin{aligned} \mu_r &= \sum_x (x - m)^r P(x) \text{ if } X \text{ is discrete} \\ &= \int_{-\infty}^{\infty} (x - m)^r f(x) dx \text{ if } X \text{ is continuous} \quad \dots (6.6.3) \end{aligned}$$

Note that, if $r=2$, then $\mu_2 = \text{Var}(X)$.

The *standard deviation* of X is denoted by σ , and is defined as

$$\sigma = \sqrt{\text{Var}(X)}$$

Example 6.6.1.

Let X be a r.v. with a density function

$$f(x) = \begin{cases} \frac{1}{b}, & 0 < x < b \\ 0 & \text{otherwise} \end{cases}$$

Then

$$m_1 = E(X) = \int_0^b \frac{x}{b} dx = \frac{b}{2},$$

$$m_2 = E(X^2) = \int_0^b \frac{x^2}{b} dx = \frac{b^2}{3}.$$

Then

$$\begin{aligned}\text{Var}(X) &= E(X^2) - [E(X)]^2 \\ &= \frac{b^2}{3} - \frac{b^2}{4} = \frac{b^2}{12}.\end{aligned}$$

The 3 - rd moment about the origin is

$$m_3 = \int_0^b \frac{x^3}{b} dx = \frac{b^3}{4}.$$

Hence the 3 - rd central moment about the mean is

$$\begin{aligned}\mu_3 &= E\left(x - m_1\right)^3 = \int_0^b \left(x - \frac{b}{2}\right)^3 \cdot \frac{1}{b} dx \\ &= \frac{\left(x - \frac{b}{2}\right)^4}{4b} \Bigg|_0^b = \frac{1}{4b} \left[\frac{b^4}{16} - \frac{b^4}{16} \right] = 0.\end{aligned}$$

Example 6.6.2.

Let X be a r.v. with a p.m.f. given by

$X = x$	0	1	2	3
$P(x)$	$\frac{1}{10}$	$\frac{2}{10}$	$\frac{3}{10}$	$\frac{4}{10}$

Then

$$\begin{aligned}m_1 &= E(X)_1 = \sum x P(x) \\ &= 0 \left(\frac{1}{10}\right) + 1 \left(\frac{2}{10}\right) + 2 \left(\frac{3}{10}\right) + 3 \left(\frac{4}{10}\right) \\ &= \frac{20}{10} = 2,\end{aligned}$$

$$\begin{aligned}
 m_2 &= E(X^2) = \sum x^2 P(x) \\
 &= 0 \left(\frac{1}{10} \right) + 1 \left(\frac{2}{10} \right) + 4 \left(\frac{3}{10} \right) + 9 \left(\frac{3}{10} \right) \\
 &= \frac{50}{10} = 5
 \end{aligned}$$

Hence

$$\begin{aligned}
 \text{Var}(X) &= E(X^2) - [E(X)]^2 \\
 &= 5 - 4 = 1
 \end{aligned}$$

The 4 - th moment about the origin is

$$\begin{aligned}
 m_4 &= \sum x^4 P(x) \\
 &= 0 \left(\frac{1}{10} \right) + 1 \left(\frac{2}{10} \right) + 16 \left(\frac{3}{10} \right) + 81 \left(\frac{4}{10} \right) \\
 &= \frac{374}{10} = 37.4
 \end{aligned}$$

The 4- th central moment about the mean $m_1 = 2$ is

$$\begin{aligned}
 \mu_4 &= E(X - 2)^4 \\
 &= \sum (x - 2)^4 P(x) \\
 &= (0 - 2)^4 \left(\frac{1}{10} \right) + (1 - 2)^4 \left(\frac{2}{10} \right) + (2 - 2)^4 \left(\frac{3}{10} \right) \\
 &\quad + (3 - 2)^4 \left(\frac{4}{10} \right) = \frac{22}{10} = 2.2
 \end{aligned}$$