

(iii) $g(x) = (x-a)^n$

$Eg(x) = E(X-a)^n$: n^{th} moment of X about the pt a

If $a = E(X)$, then

$E(X - E(X))^n = \mu_n$: n^{th} order central moment of X

$n=2$; $\mu_2 = E(X - E(X))^2 \rightarrow \text{variance of } X$
 $= \sigma^2$

$\mu_2^{1/2} = \sigma$: standard deviation of X

Remark: Measure of skewness

$$Y_1 = \frac{\mu_3}{\sigma^3} = \left(\frac{\mu_3}{\mu_2^{3/2}} \right)^{1/2} = \frac{\mu_3}{(\sigma^2)^{3/2}} = \frac{\mu_3}{\sigma^3}$$

$= 0$ for distⁿ sym about $E(X)$

> 0 for positively skewed distⁿ

< 0 for negatively skewed distⁿ

Remark: Measure of peakedness.

Kurtosis measure $Y_2 = \frac{\mu_4}{\sigma^4}$

Remark: If g_1, g_2, \dots, g_r be r real valued fⁿs on \mathbb{R} and

let X be a r.v. $\Rightarrow E g_i(X)$ exists for $i=1, \dots, r$, then

$E \left(\sum_{i=1}^r g_i(X) \right)$ exists and is equal to $\sum_{i=1}^r E g_i(X)$

e.g: $\mu_n = E(X - E(X))^n$

$$= E \left(X^n + \binom{n}{1} X^{n-1} (-E(X)) + \binom{n}{2} X^{n-2} (-E(X))^2 + \dots + (-1)^n E(X)^n \right)$$

i.e. $\mu_n = \mu_n' - \binom{n}{1} \mu_{n-1}' \mu_1' + \binom{n}{2} \mu_{n-2}' (\mu_1')^2 - \dots + (-1)^n (\mu_1')^n$

$$n=2$$

$$\begin{aligned}\sigma^2 &= \mu_2 = E(X - E(X))^2 \\ &= \mu_2' - 2(\mu_1')^2 + (\mu_1')^2 \\ &= \mu_2' - (\mu_1')^2 \\ &= EX^2 - (E(X))^2\end{aligned}$$

Remark: Suppose EX^m exists for a positive int m
then \forall positive int $K \exists K \leq m$, EX^K exists

$$\int_{-\infty}^{\infty} |x|^K f(x) dx = \int_{|x| \leq 1} |x|^K f(x) dx + \int_{|x| \geq 1} |x|^K f(x) dx$$

(for cont case)

$$\leq \int_{|x| \leq 1} f(x) dx + \int_{|x| > 1} |x|^K f(x) dx$$

$$\leq \int_{|x| \leq 1} f(x) dx + \int_{|x| > 1} |x|^m f(x) dx$$

$$\leq \int_{-\infty}^{\infty} f(x) dx + \int_{-\infty}^{\infty} |x|^m f(x) dx$$

$$= 1 + E|X|^m < \infty$$

$\Rightarrow EX^K$ exists.

Moment Generating function (m.g.f)

Defⁿ: Let X be r.v. The function

$M_X(t) = E(e^{tx})$ is known as the m.g.f of the r.v. X if the expectation exists in some neighborhood of origin

Note: If m.g.f. exists, it determines the d.f. uniquely.

Note: Suppose all derivatives of $M_X(t)$ exists at $t=0$ and can be obtained by differentiating under the expectation, then

$$\left. \frac{\partial^k}{\partial t^k} M_X(t) \right|_{t=0} = \left. \frac{\partial}{\partial t^k} E(e^{tx}) \right|_{t=0}$$

$$= E \left(\left. \frac{\partial^k}{\partial t^k} e^{tx} \right|_{t=0} \right)$$

$$= E \left(x^k e^{tx} \right)_{t=0} = \mu'_k$$

i.e. $M_X(t)$ generates the moments of X .

Note: Taylor series expansion of $M_X(t)$ about 0 gives

$$M_X(t) = M_X(0) + \frac{M_X'(0)}{1!} t + \frac{M_X''(0)}{2!} t^2 + \dots$$

$$\text{Coeff of } \frac{t^k}{k!} = \mu'_k = E X^k$$

Note: Although m.g.f. exists for most of the common distributions, there are cases when it does not exist
e.g. a Cauchy distⁿ

$$f(x) = \frac{1}{\pi} \cdot \frac{1}{1+x^2}; \quad x \in \mathbb{R}$$

Some standard inequalities

(1) Chebyshev's inequality

X is a r.v. with $E(X) = \mu$ and $V(X) = \mu_2 = \sigma^2$

$$P(|X - \mu| \geq \epsilon) \leq \frac{\sigma^2}{\epsilon^2} \quad \forall \epsilon > 0$$

(2) Generalisation of Chebyshev's inequality

$h: \mathbb{R} \rightarrow \mathbb{R}$ be non-negative fⁿ $E h(X)$ is finite.

Then $\forall c > 0$

$$P(h(X) \geq c) \leq \frac{E h(X)}{c}; \quad h(x) = |x|^r \text{ gives Markov's inequality}$$

(3) Let g be a non-negative and strictly increasing function
 $g: [0, \infty) \rightarrow \mathbb{R}$

such that $E g(X)$ is finite, then for any $c > 0 \Rightarrow$

$$g(c) > 0$$

$$P(|X| \geq c) \leq \frac{E(g(|X|))}{g(c)}$$

(4) Jensen's inequality

Let $\psi: (a, b) \rightarrow \mathbb{R}$ be a convex function and let X be r.v.

with d.f. F having support $S \subseteq (a, b)$.

Then

$$E \psi(X) \geq \psi(E(X))$$

provided the expectations exist.

Note : From Jensen's inequality it follows that, for any r.v. X

$$E X^2 \geq (E X)^2$$

$$E |X| \geq |E(X)|$$

$$E e^X \geq e^{EX}$$

For r.v. $X \ni P(X > 0) = 1$

$$E(\ln X) \leq \ln(E X)$$

Quantile & percentile

Defⁿ: Let $0 < p < 1$. The quantile of order p of the distⁿ of a r.v. X , say z_p , is a point \ni

$$P(X < z_p) \leq p \text{ and } P(X \leq z_p) \geq p$$

z_p is also called the $(100 \times p)\%$ percentile

Note : z_p is \ni

$$P(X \leq z_p) \geq p \text{ and } P(X \geq z_p) \geq 1-p$$

$$\left(\begin{array}{l} \downarrow \\ 1 - P(X < z_p) \geq 1-p \\ \text{i.e. } P(X < z_p) \leq p \end{array} \right)$$

Further

$$\text{i.e. } P(X \leq z_p) - P(X = z_p) \leq p$$

~~$$P(X < z_p) \leq p$$~~

$$p \leq P(X \leq z_p) \leq p + P(X = z_p)$$

Note: For a continuous distⁿ z_p is thus solution of

$$F(z_p) = p$$

If $F(\cdot)$ is strictly increasing then solⁿ is unique, o/w there can be many solutions.