

More commonly used form

Suppose  $x$  is a RV then  $(x-u)^2$  is also a RV

st  $(x-u)^2 \geq 0 \quad \forall x \in S$  [Here  $u$  represents the mean]

$\therefore$  apply the previous result

$$\Pr((x-u)^2 \geq c) < \frac{E[(x-u)^2]}{c}$$

$$\Pr(|x-u| \geq \sqrt{c}) < \frac{\sigma^2}{c}$$

$$\text{Let } \sqrt{c} = k\sigma$$

$$c = k^2 \sigma^2$$

$$\Rightarrow \boxed{\Pr(|x-u| \geq k\sigma) < \frac{1}{k^2}}$$

This can be equivalent

$$\Pr(|x-u| < k\sigma) > 1 - \frac{1}{k^2}$$

$$\Rightarrow \overset{\text{Use}}{\cancel{1 - \Pr}} 1 - \Pr(|x-u| \geq k\sigma) = \Pr(|x-u| < k\sigma)$$

## Chebyshev's Inequality

Let  $x$  be a non-negative RV if  $E[x]$  exist

then

$$Pr[x \geq c] \leq \frac{E[x]}{c}$$

$\Rightarrow$  we are going to prove for discrete case [continuous can be handled in a similar way]

$$E[x] = \sum_{x_i \in S} x_i f(x_i)$$

$S \subseteq \mathbb{R}_+$  only positive real numbers

choose  $c \in S$

$$E[x] = \sum_{\substack{x_i < c \\ x_i \in S}} x_i f(x_i) + \sum_{\substack{x_i \geq c \\ x_i \in S}} x_i f(x_i) \geq \sum_{\substack{x_i \geq c \\ x_i \in S}} x_i f(x_i)$$

$\parallel$   
 $\text{+ve}$

$$\geq c \sum_{x_i \geq c} f(x_i) \quad [As \ x_i \geq c]$$

$$E[x] \geq c Pr[X \geq c]$$

$$\boxed{Pr(x \geq c) \leq \frac{E[x]}{c}}$$



$$\frac{d}{dt} \ln M(t) = \frac{M'(t)}{M(t)} \Big|_0 = \frac{E[X]}{1} =$$

$$\begin{aligned} \frac{d^2}{dt^2} \ln M(t) &= \frac{d}{dt} \left[ \frac{M'(t)}{M(t)} \right] = \frac{M''(t)M(t) - M'(t)^2}{M(t)^2} \Big|_0 \\ &= \frac{M''(t)M(t) - M'(t)^2}{M(t)^2} \Big|_0 = \frac{E[X^2] - E[X]^2}{1} \\ &= \sigma^2 \end{aligned}$$

#### 4) Characteristic function

~~Unlike Moment generating function~~ characteristic function  
It is defined as:-

$$E[e^{ixt}]$$

Unlike moment generation func<sup>n</sup> if exist for all t

$$\left| \int_{-\infty}^{\infty} e^{ixt} f(x) dx \right| \leq \int_{-\infty}^{\infty} f(x) dx$$

$|e^{ixt}| \leq 1$

Note :- Moment generation functions are unique for a distribution if 2 distributions have same MGF then they are same.

Let  $\sigma^2$  denote the variance

$$\sigma^2 = E[(x - \mu)^2]$$

$$= E[x^2 - 2x\mu + \mu^2]$$

Now  $E$  is a linear function

$$\Rightarrow \sigma^2 = E[x^2] - 2E[x]\mu + \mu^2$$

$$E[x] = \mu$$

$$\boxed{\sigma^2 = E[x^2] - \mu^2}$$

$$\text{Standard deviation} = \sqrt{\sigma^2}$$

3) Moment generating function :-

Suppose  $\exists h > 0$  st  $E[e^{tx}]$  exist for  $t \in (-h, h)$

Then

$$E[e^{tx}] = \int_{-\infty}^{\infty} e^{tx} f(x) dx = M(t)$$

$$M(0) = 1$$

$$M'(0) = \mu$$

$$M''(0) = E[x^2]$$

and so on.



## Some special Expectation

Note

Expectation are linear functions.

Linear function: Suppose  $f: U \rightarrow V$  st and  $\alpha \in \text{Scalars}$

$$f(u+v) = f(u) + f(v)$$

$$f(\alpha u) = \alpha f(u)$$

Or simply

$$f(\alpha u + \beta v) = \alpha f(u) + \beta f(v)$$

1) Let  $X$  be a discrete RV then  $[f \text{ be the pmf}]$

$$E[X] = \sum_x x f(x)$$

This is called the mean of the distribution  $X$  usually represented as  $\mu$  [Similar result can be obtained for continuous distribution.]

$$E[X] = \int_S x f(x) dx$$

$S$  represents the support

2) Another special expectation is obtained by  $E[(X - \mu)^2]$  here  $\mu$  is the mean of the distribution. This expected value is called Variance.