

### \* Arithmetic mean ( $\bar{x}$ )

$$\bar{x} = \frac{x_1 + x_2 + \dots + x_n}{n} = \frac{\sum x_i}{N}$$

$$\bar{x} = \frac{x_1 f_1 + x_2 f_2 + \dots + x_n f_n}{n} = \frac{\sum x_i f_i}{N}$$

### \* Assumed mean method

for continuous frequency distribution

$$d_i = x_i - A$$

$$\Rightarrow \bar{x} = A + \frac{1}{N} \sum f_i d_i$$

$$d_i = \frac{x_i - A}{h}$$

$$\Rightarrow \bar{x} = A + \frac{h}{N} \sum f_i d_i$$

### \* Median

- i) find  $N$ , where  $N = \sum f_i$
- ii) find the observation where C.f is just greater than  $N/2$
- iii) corresponding  $x_i$  is a median ( $x$ )

for continuous frequency distribution

iii) corresponding class is median class ( $l-h$ )

$$\text{Median} = l + \frac{h}{f} \left( \frac{N}{2} - C.f \right)$$

$\swarrow$   $\downarrow$   $\downarrow$   
 gap ( $h-l$ ) frequency of Median class Cumulative frequency of class preceding median class.

### \* Mode

$\hookrightarrow$  (i.e) corresponding to maximum frequency.

for continuous

corresponding class is modal class ( $l-h$ ) with frequency ( $f_1$ )

$$\text{Mode} = l + \frac{h}{(2f_1 - f_0 - f_2)} (f_1 - f_0)$$

$$\text{Mode} = 3 \text{Median} - 2 \text{Mean}$$

\* Geometric Mean ( $G$ )

$$G = (\alpha_1 \times \alpha_2 \times \alpha_3 \times \dots \times \alpha_n)^{1/n}$$

\* Harmonic Mean ( $H$ )

$$\frac{1}{H} = \frac{\frac{1}{\alpha_1} + \frac{1}{\alpha_2} + \frac{1}{\alpha_3} + \dots + \frac{1}{\alpha_n}}{n}$$

\*  $(A.M.) \times (H.M.) = (G.M.)^2$

\*  $a$  &  $b \Rightarrow A.M. = \frac{a+b}{2}, G.M. = \sqrt{ab}, H.M. = \frac{2ab}{a+b}$

\* ~~Mean~~ Standard deviation ( $\sigma^2$ )

$$\sigma^2 = \frac{1}{N} \sum f_i (x_i - \bar{x})^2 = \frac{1}{N} \sum f_i x_i^2 - [\bar{x}]^2$$

if  $d_i = x_i - A$

$$\Rightarrow \sigma_d^2 = \frac{1}{N} \sum f_i d_i^2 - \left[ \frac{1}{N} \sum f_i d_i \right]^2$$

if  $d_i = (x_i - A)/h$

$$\Rightarrow \sigma_x^2 = \frac{h^2}{N} \sum f_i d_i^2 - \left[ \frac{h}{N} \sum f_i d_i \right]^2 = h^2 \sigma_d^2$$

\* Coefficient of Variance (COV)

$$\Rightarrow \frac{\sigma}{\bar{x}} \times 100$$

\*  $\begin{matrix} \sigma_1, \bar{x}_1 \\ f_1 \end{matrix} \quad \begin{matrix} \sigma_2, \bar{x}_2 \\ f_2 \end{matrix} \quad \begin{matrix} \sigma_3, \bar{x}_3 \\ f_3 \end{matrix}$

$$\Rightarrow \bar{x} = \frac{\bar{x}_1 \times f_1 + \bar{x}_2 \times f_2 + \bar{x}_3 \times f_3}{f_1 + f_2 + f_3}$$

$$\Rightarrow \sigma^2 = \frac{f_1(\sigma_1^2 + d_1^2) + f_2(\sigma_2^2 + d_2^2) + f_3(\sigma_3^2 + d_3^2)}{f_1 + f_2 + f_3}$$

$$\Rightarrow d_1 = \bar{x} - \bar{x}_1, d_2 = \bar{x} - \bar{x}_2, d_3 = \bar{x} - \bar{x}_3.$$



### \* Probability

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

$$P(A/B) = \frac{P(A \cap B)}{P(B)} \quad \& \quad P(B/A) = \frac{P(A \cap B)}{P(A)}$$

↓  
probability of happening of event 'A' given that event 'B' has already completed.

if A & B are independent events  $\Rightarrow P(A \cap B) = P(A) \times P(B)$

→ Difference between mutually exclusive events and independent events is that in mutually exclusive case, we have 2 events that cannot occur at same time whereas incase of independent event one event remains unaffected by the occurrence of other event.

⊛  $X = \{HHH, HHT, HTH, THH, TTH, THT, HTT, TTT\}$

$X(\text{No. of Heads})$	0	1	2	3
$P(X)$	$1/8$	$3/8$	$3/8$	$1/8$

Random Variable (discrete)

Table. probability distribution.

→ P.m.f (Probability mass function)  $\Rightarrow P_i \geq 0 \quad \& \quad \sum P_i = 1$

$$F(x_i) = \sum P_i \text{ where } P(X \leq x_i) \Rightarrow F(x) = \begin{cases} 1/8 & x \leq 0 \\ 4/8 & x \leq 1 \\ 7/8 & x \leq 2 \\ 1 & x \leq 3 \end{cases}$$

→ Distribution function / (c.d.f)  
Cumulative distribution function.

### ⊛ continuous random variable

Probability density function (p.d.f)  $[f(x)]$

i)  $\int_{-\infty}^{\infty} f(x) dx = 1$       ii)  $f(x) \geq 0, -\infty < x < \infty$

a) Arithmetic mean  $= \int_a^b x f(x) dx$

b) Geometric mean (G)  $\Rightarrow \log G = \int_a^b \log x f(x) dx$

c) Harmonic mean (H)  $\Rightarrow \frac{1}{H} = \int_a^b \frac{f(x)}{x} dx$

d)  $\mu'_2$  (about origin)  $= \int_a^b x^2 f(x) dx$ ;  $\mu'_2$  (about mean)  $= \int_a^b (x - \bar{x})^2 f(x) dx$   
Mean

$$\therefore \mu_2 = \mu'_2 - (\mu'_1)^2$$

$$\therefore \mu_3 = \mu'_3 - 3\mu'_2\mu'_1 + 2(\mu'_1)^3$$

$$\therefore \mu_4 = \mu'_4 - 4\mu'_3\mu'_1 + 6\mu'_2\mu_1^2 - 3(\mu'_1)^4$$

$$\therefore \text{Mean} = \mu'_1$$

$$\text{Variance} = \mu_2 \text{ (raw)}$$

$$\int_a^{Q_1} f(x) dx = \frac{1}{4} ; \int_a^{Q_3} f(x) dx = \frac{3}{4}$$

Page No.:

Date:

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e) Median (M)  $\rightarrow$  Divides distribution into 2 parts.

$$\int_a^M f(x) dx = \int_M^b f(x) dx = \frac{1}{2}$$

f) Mode  $\rightarrow$   $f(x)$  is maximum

$$\Rightarrow f'(x) = 0 \text{ \& } f''(x) < 0$$

\* g) Probability  $P(E) = \int_E f(x) dx \rightarrow$

i) continuous/cumulative distribution function  $[F(x)]$

$$\Rightarrow F(x) = P(X \leq x) = \int_{-\infty}^x f(x) dx, -\infty < x < \infty$$

$$\Rightarrow \frac{dF(x)}{dx} = f(x).$$

$$\Rightarrow P(a < x < b) = \int_a^b f(x) dx = \int_{-\infty}^b f(x) dx - \int_{-\infty}^a f(x) dx$$

$$= P(X \leq b) - P(X \leq a) = \underline{F(b) - F(a)}$$



### ⊛ Covariance

$$\begin{aligned}\text{Cov}(X, Y) &= E[\{X - E(X)\}\{Y - E(Y)\}] \\ &= E(XY) - E(X) \cdot E(Y)\end{aligned}$$

if  $X$  &  $Y$  are independent  $\Rightarrow E(XY) = E(X) \cdot E(Y)$   
 $\Rightarrow \text{Cov}(X, Y) = 0$  if  $X$  &  $Y$  are independent.

- ⊛
1.  $\text{Cov}(X+a, Y+b) = \text{Cov}(X, Y)$
  2.  $\text{Cov}(aX, bY) = ab \text{Cov}(X, Y)$
  3.  $\text{Cov}(X+Y, Z) = \text{Cov}(X, Z) + \text{Cov}(Y, Z)$

$$\text{Correlation Coefficient}(X, Y) = \frac{\text{Cov}(X, Y)}{\sigma_X \times \sigma_Y}$$

\* if  $U = a_1X_1 + a_2X_2 + \dots + a_nX_n$

$$\begin{aligned}E(U) &= a_1E(X_1) + a_2E(X_2) + \dots + a_nE(X_n) \\ U - E(U) &= a_1[X_1 - E(X_1)] + a_2[X_2 - E(X_2)] + \dots + a_n[X_n - E(X_n)] \\ E[U - E(U)]^2 &= a_1^2 E[X_1 - E(X_1)]^2 + a_2^2 E[X_2 - E(X_2)]^2 + \dots + a_n^2 E[X_n - E(X_n)]^2 \\ &\quad + 2 \sum_{i=1}^n \sum_{j=1}^n a_i a_j E[\{X_i - E(X_i)\}\{X_j - E(X_j)\}]\end{aligned}$$

$$\Rightarrow V(U) = a_1^2 V(X_1) + a_2^2 V(X_2) + \dots + a_n^2 V(X_n) + 2 \sum_{i=1}^n \sum_{j=1}^n a_i a_j \text{Cov}(X_i, X_j)$$

$$\Rightarrow V(X_1 + X_2 + \dots + X_n) = V(X_1) + V(X_2) + \dots + V(X_n) + 2 \sum_{i=1}^n \sum_{j=1}^n \text{Cov}(X_i, X_j)$$

if  $X_1, X_2, \dots, X_n$  are independent  $\Rightarrow \text{Cov}(X_i, X_j) = 0$

$$\Rightarrow V(X_1 + X_2 + \dots + X_n) = V(X_1) + V(X_2) + \dots + V(X_n)$$

⊛  $V(X_1 \pm X_2) = V(X_1) + V(X_2) \pm 2\text{Cov}(X_1, X_2)$

if  $X_1$  &  $X_2$  are independent

$$\Rightarrow V(X_1 \pm X_2) = V(X_1) + V(X_2)$$

### ⊛ Moment generating function ( $M_X(t)$ )

$$\begin{aligned}\Rightarrow M_X(t) &= E(e^{tx}) = \int_{-\infty}^{\infty} e^{tx} f(x) dx, \text{ continuous} \\ &= \sum_{-\infty}^{\infty} e^{tx} f(x), \text{ discrete}\end{aligned}$$

⊛  $M_{cX}(t) = M_X(ct)$

⊛  $M_{X_1+X_2+\dots+X_n}(t) = M_{X_1}(t) \times M_{X_2}(t) \times \dots \times M_{X_n}(t)$   $\rightarrow$  Additive property of distribution



## Fitting a Binomial

→ take mean & equate with  $np$   
the  $f_e = N \times P(x)$

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Date: _____
Page: _____

- ⊛ Uniqueness theorem of Moment generating function  
 ↳ The moment generating functions of a distribution uniquely determines the distribution.

$$\mu_1' = E(X) = \left. \frac{d(M_X(t))}{dt} \right|_{t=0}$$

$$\mu_2' = E(X^2) = \left. \frac{d^2(M_X(t))}{dt^2} \right|_{t=0}$$

\* Mean =  $E(X) = \mu_1'$  , \* Variance =  $E(X^2) - [E(X)]^2 = \mu_2' - (\mu_1')^2$

$$\Rightarrow \mu_2' = E(X^2) = \left. \frac{d^2(M_X(t))}{dt^2} \right|_{t=0}$$

- ⊛ Bernoulli Distribution  $\frac{p}{q} \rightarrow 1$  ,  $p+q=1$

$$\mu_2' = E(X^2) = 0^2 \times q + 1^2 \times p = p$$

$$\Rightarrow \text{Mean} = E(X) = p \quad \& \quad \text{Variance} = E(X^2) - [E(X)]^2 = p - p^2 = p(1-p) = pq$$

- ⊛ Binomial Distribution

$$P(x) = {}^nC_x p^x q^{n-x} ; x=0,1,\dots,n ; p+q=1$$

$$= 0 ; \text{otherwise}$$

$$\rightarrow \sum P(x) = \sum {}^nC_x p^x q^{n-x} = (p+q)^n = 1$$

Conditions

- i) Only 2 possible outcomes (p & q) i.e. success & failure
- ii) 'n' is finite
- iii) each trial is independent of each other
- iv) p & q are constant throughout experiments.

$$\rightarrow \mu_1 = np , \mu_2 = n(n-1)p^2 + np , \mu_3 = n(n-1)(n-2)p^3 + n(n-1)p^2 + np$$

$$\text{Mean } E(X) = \mu_1 = np , \text{ Variance } = \mu_2 - \mu_1^2 = npq$$

mode =  $\lfloor (n+1)p \rfloor$   
 if integer then  
 2 modes  $(n+1)p, (n+1)p-1$

→ Moment generating function

$$M_X(t) = E[e^{tx}] = \sum {}^nC_x e^{tx} p^x q^{n-x} = \sum {}^nC_x (e^t p)^x q^{n-x} = (pe^t + q)^n$$

$$\rightarrow \text{recurrence relation} \rightarrow \frac{P(x)}{P(x-1)} = \frac{n-x+1}{x} \times \left(\frac{p}{q}\right)$$



### ⊕ Poisson Distribution

→ when  $n \rightarrow \infty$  &  $p \rightarrow 0$  but  $\lambda = np$  (finite constant)

$$P(x) = \frac{e^{-\lambda} \lambda^x}{x!}, \quad x=0,1,\dots$$

$= 0$ , otherwise

(rate)

$$\rightarrow \sum P(x) = \sum \frac{e^{-\lambda} \lambda^x}{x!} = e^{-\lambda} \left( 1 + \lambda + \frac{\lambda^2}{2!} + \dots \right) = e^{-\lambda} \cdot e^{\lambda} = 1$$

$$\rightarrow \text{Mean} = \lambda, \text{ Variance} = \lambda$$

$$\rightarrow \text{Mode} = [\lambda], \text{ when } \lambda \text{ is not integer}$$

$$= \lambda \text{ \& } \lambda - 1$$

$$\rightarrow \text{Recurrence relation} \Rightarrow \frac{P(x)}{P(x-1)} = \frac{\lambda}{x}$$

$$\rightarrow \text{MGF } (M_x(t)) \Rightarrow M_x(t) = E(e^{tx}) = \sum e^{tx} \times \frac{e^{-\lambda} \lambda^x}{x!}$$

$$\Rightarrow M_x(t) = e^{-\lambda} \sum \frac{(\lambda e^t)^x}{x!} = e^{-\lambda} (e^{\lambda e^t})$$

$$\Rightarrow M_x(t) = e^{-\lambda} \cdot e^{\lambda e^t} \Rightarrow e^{\lambda(e^t - 1)}$$

### ⊕ Negative Binomial Distribution

→  $P(x; r, p)$  → probability of 'x' failures preceeding r<sup>th</sup> success in (x+r) trials.

$$\begin{array}{c} \text{x failures} \\ \text{r-1 success} \end{array} \uparrow \Rightarrow P(x) = \binom{x+r-1}{r-1} p^{r-1} q^x, \quad x=0,1,\dots$$

$= 0$ , otherwise.

$$\text{let } p = \frac{1}{\phi} \text{ \& } q = \frac{p}{\phi}$$

$$\Rightarrow \text{M.G.F} = (\phi - pe^t)^{-r}, \quad \text{Mean} = \frac{rP}{(E(x))}, \quad \text{Variance} = \frac{rP\phi}{(V(x))}$$



### ⊛ Geometric Distribution

→ probability that there are 'x' failures preceding first success

$$P(x) = q^x p, \quad x = 0, 1, 2, \dots$$

$$= 0 \quad \text{otherwise}$$

$$\text{M.G.F.}(M_X(t)) = E[e^{xt}] = \sum_{x=0}^{\infty} q^x p \times e^{xt}$$

$$= \sum_{x=0}^{\infty} (qe^t)^x p = p \times \frac{1}{1 - qe^t} = \frac{p}{1 - qe^t}$$

\* Mean =  $\frac{q}{p}$ , Variance =  $\frac{q}{p^2}$

### ⊛ Lack of Memory

→  $P(Y=t | X \geq k) = pq^t$ , where  $Y = X - k$

### ⊛ Normal Distribution $\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

$$f(x; \mu) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

→ P.d.f of Normal Distribution  $\sim N(\mu, \sigma^2)$

→ standard Normal Variate  $(Z) = \frac{X - \mu}{\sigma}$

→  $E(Z) = 0$  &  $\text{Var}(Z) = 1 \Rightarrow Z \sim N(0, 1)$

P.d.f of  $Z \Rightarrow \phi(z) = \frac{e^{-z^2/2}}{\sqrt{2\pi}}$

$\phi(-z) = P(Z \leq -z) = P(Z \geq z) = 1 - P(Z \leq z) = 1 - \phi(z)$

distribution function of  $Z \Rightarrow F(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-t^2/2} dt$

$F(-z) = 1 - F(z)$

→  $[P(x)]_{\max}$  at  $x = \mu$

→  $M_{2n+1} = 0$  &  $M_{2n} = \frac{(2n-1)!!}{2^n} \sigma^{2n}$

→ point of inflection  $\Rightarrow x = \mu \pm \sigma$

→ Mean, Mode & Median coincide & are equal to  $\mu$ .

→ M.G.F.  $(M_X(t)) = e^{\mu t + \frac{t^2 \sigma^2}{2}}$  of  $f(x)$

M.G.F.  $(M_X(t)) = e^{\frac{t^2}{2}}$  of standard normal variate  $(Z = \frac{X - \mu}{\sigma})$

→ Mean at point A  $\Rightarrow \mu_0 = \mu_1 + A$



### \* Central limit theorem

if  $X_1, X_2, \dots, X_n$  are independent random variables with  $\text{Mean} = \mu_i$  &  $\text{Variance} = \sigma_i^2$

then under general conditions

$S_n = \sum_{i=1}^n X_i$  follows normal distribution  $n \rightarrow \infty$

with  $\mu = \sum \mu_i$  &  $\sigma^2 = \sum \sigma_i^2$

→  $n \geq 30$  is considered large.

### \* Continuous approximation of $X$ .

$$P(X \leq x) = P(\text{continuous } X < x + 0.5)$$

$$P(x \leq X) = P(x - 0.5 < X)$$

$$P(X = x) = P(x - 0.5 < X < x + 0.5)$$

### \* Estimator & Sampling Distribution

→ Standard deviation of  $\bar{x} = \frac{\text{Population S.D.}}{\sqrt{\text{Sample Size}}} = \frac{\sigma}{\sqrt{n}}$

→ S.N.V (t) =  $\frac{\bar{x} - \mu}{\left(\frac{\sigma}{\sqrt{n}}\right)}$  → mean  
standard deviation of  $\bar{x}$

→ Population proportion (P) & sample proportion (p)

Mean of  $p = p = \underline{P}$

Standard deviation of  $p = \sqrt{\frac{PQ}{n}}$

→ S.N.V (t) =  $\frac{\bar{p} - P}{\sqrt{\frac{PQ}{n}}}$

→ Standard Error =  $\sqrt{\frac{PQ}{n}}$  & estimate of S.E =  $\sqrt{\frac{pq}{n}}$

→ Unbiased estimator of population variance ( $\sigma^2$ ) =  $\left(\frac{n}{n-1}\right) s^2$

where  $s^2 = \frac{\sum x^2}{n} - \left(\frac{\sum x}{n}\right)^2$



\* Confidence level

i) 95%  $\Rightarrow \left( p - 1.96 \sqrt{\frac{pq}{n}}, p + 1.96 \sqrt{\frac{pq}{n}} \right)$

99%  $\Rightarrow 2.58$

for almost certainty  $\Rightarrow 3$

\* Maximum likelihood

$$L = \prod_{i=1}^N f(x_i, \alpha)$$

i) take log on both sides  $\ln L = \sum_{i=1}^N \ln(f(x_i, \alpha))$

ii)  $\left. \frac{\partial \ln L}{\partial \alpha} \right|_{\max} = 0$

iii) we have value of parameter  $\alpha$ .

\* Unbiasedness ( $E(T(x))$ )

\* Efficiency  $\rightarrow$  i) unbiasedness  
ii) min. variance

\* M.V.U.E  $\rightarrow$  PATA NHI KYA HAI YE?



① Chi-Square test ( $\chi^2$ )  $\xrightarrow{*}$  No parent parameters  
 \* Goodness of fit (Non-parametric tests & Distribution free test).

Conditions  $\Rightarrow N > 50$  &  $f_i \geq 5$

$$\chi^2 = \sum_{i=1}^n \left[ \frac{(O)_i - (E)_i}{(E)_i} \right]^2 \quad \& \quad \sum_{i=1}^n O_i = \sum_{i=1}^n E_i$$

\* for a  $2 \times 2$  table.

a	b	a+b
c	d	c+d
a+c	b+d	

$$\chi^2 = \frac{N(ad-bc)^2}{(a+b)(a+c)(b+d)(c+d)}, \quad \chi^2 = \frac{N[|ad-bc| - N/2]^2}{(a+b)(a+c)(b+d)(c+d)}$$