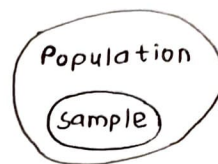


Statistics-1

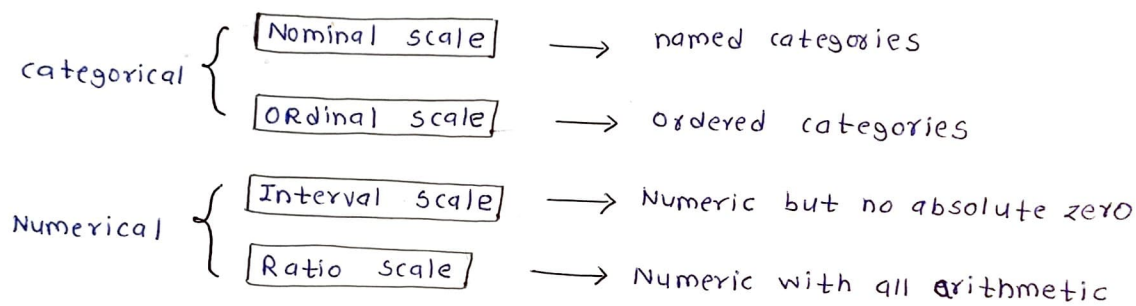
* Basics :

- 2 branches : (a) Descriptive statistics
(b) Inferential statistics



- Cross-sectional data : data collected at a point of time
Time-series data : data collected over a period of time

- scales of measurement / data types :



* Categorical Data :

- Frequency distribution table / Relative frequency table
- charts : (a) Pie chart
(b) Bar chart
(c) Pareto chart (frequency sorted bar chart)
- mode : Variable / Category with max. frequency
median : Variable / category of middle observation
- continuous data category:
 - 20-30 : 20 is included but 30 does not.
upper limit is 30 and lower limit is 20.
10 is class width. (i.e. $30-20=10$)
25 is class mark. (i.e. $\frac{20+30}{2}=25$)

* Numerical Data:

→ Sample size : n

Sample mean : \bar{x}

Sample S.D. : S

Population size : N

Population mean : μ

Population S.D. : σ

→ Mean : $\frac{\sum f_i m_i}{\sum f_i}$ or $\frac{\sum x_i}{n}$

→ Adding constant : $y_i = x_i + c \Rightarrow \bar{y} = \bar{x} + c$

Multiplying with constant : $y_i = c x_i \Rightarrow \bar{y} = c \bar{x}$

→ Median : middle value in ordered List

(a) n is odd : $\frac{n+1}{2}^{\text{th}}$ observation.

(b) n is even : average of $\frac{n}{2}^{\text{th}}$ and $\frac{n}{2}+1^{\text{th}}$ observation.

→ Adding constant : New median = old median + c

Multiplying with constant : New median = $c \times$ old median

→ Mode : most frequently occurring value

→ Adding constant : New mode = old mode + c

Multiplying with constant : New mode = $c \times$ old mode

→ Range : Diff. of largest & smallest value

→ Variance : Let $x_i - \bar{x}$ is deviation.

$$s^2 = \frac{(x_1 - \bar{x})^2 + (x_2 - \bar{x})^2 + \dots + (x_n - \bar{x})^2}{n-1}$$

$$\sigma^2 = \frac{(x_1 - \mu)^2 + (x_2 - \mu)^2 + \dots + (x_N - \mu)^2}{N}$$

→ Adding constant : New variance = old variance

Multiplying with constant : New variance = $c^2 \times$ old variance

→ Standard Deviation : Positive Square root of Variance

→ Adding constant : New S.D. = Old S.D.

Multiplying with constant : New S.D. = $C \times$ Old S.D.

→ measure of central tendency : Mode, Median & Mean

measure of dispersion/spread : Variance & S.D.

→ Percentile : x percentile means $x\%$ of data are \leq it and;
 $(100-x)\%$ of data are \geq it.

→ First / Lower Quartile (25th percentile) (Q_1)

Second / Median Quartile (50th percentile) (Q_2)

Third / Upper Quartile (75th percentile) (Q_3)

* Five-Number Summary :

1. Minimum

2. Q_1

3. Q_2

4. Q_3

5. Maximum

$$IQR = Q_3 - Q_1$$

* Scatter Plot :

→ x-axis : Explanatory / Independent variable

y-axis : Responsive / Dependent variable

→ Gives insight about association

→ Covariance and correlation are measure of linear association.

* Covariance :

$$\rightarrow \text{Population's covariance} = \frac{\sum_{i=1}^N (x_i - \bar{\mu}_x)(y_i - \bar{\mu}_y)}{N}$$

$$\text{Sample's covariance} = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{n-1}$$

\rightarrow If covariance $> 0 \Rightarrow$ Positive association
covariance $< 0 \Rightarrow$ Negative association

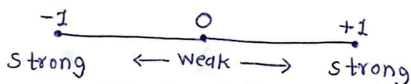
\rightarrow Covariance has unit i.e. unit of $x_i \times$ unit of y_i

* Correlation :

$$\rightarrow \text{Pearson correlation } \rho = \frac{\text{Covariance}}{\text{S.D. of } x_i \times \text{S.D. of } y_i}$$

$$\therefore \rho = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2} \sqrt{\sum (y_i - \bar{y})^2}}$$

Range (ρ) is $[-1, 1]$



\rightarrow Correlation coefficient does not have any units.

$\rightarrow \rho^2$ or R^2 gives goodness of straight line / curve fitting. $R^2 \in [0, 1]$

* Association b/w numeric and categorical variables:

→ Point-Biserial correlation coefficient r_{ps}

$$r_{ps} = \left(\frac{\bar{Y}_0 - \bar{Y}_1}{S_x} \right) \sqrt{P_0 P_1}$$

where; P_0 = Proportion of categorical variable coded with 0

P_1 = Proportion of categorical variable coded with 1

\bar{Y}_0 = mean of categorical variable coded with 0

\bar{Y}_1 = mean of categorical variable coded with 1

S_x = S.D. of numerical variable

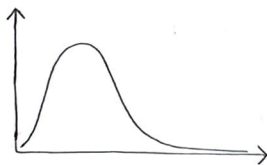
* Infinite series:

$$\rightarrow \sum_{n=0}^{\infty} ar^n = \frac{a}{1-r} \quad \text{where } |r| < 1$$

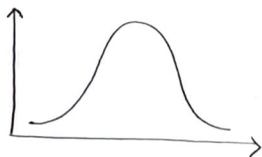
$$\rightarrow \sum_{n=0}^{\infty} \left(\frac{x^n}{n!} \right) = e^x$$

* Distributions:

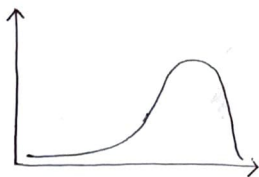
(a) Right skewed
(Positively skewed)



(b) Symmetric



(c) Left skewed
(Negatively skewed)



* Permutation:

→ Definition: Ordered arrangement of all or r objects from n .

$${}_nP_r = \frac{n!}{(n-r)!} \quad (\text{without repetition})$$

$$= n^r \quad (\text{with repetition})$$

→ Non-distinct permutation:

$${}_nP_n = \frac{n!}{P_1! P_2! \dots P_k!} \quad \text{where } P_i = \text{group of same objects}$$

→ Circular permutation:

cw & ccw are considered different = $(n-1)!$

cw & ccw are considered same = $\frac{(n-1)!}{2}$

* Combination:

→ Definition: Selecting / choosing r objects from n .

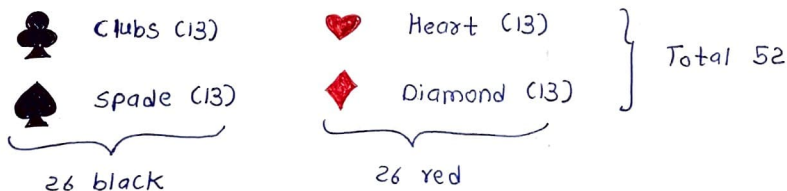
$${}_nC_r = \frac{{}_nP_r}{r!} \quad \text{or} \quad \frac{n!}{r!(n-r)!}$$

→ Identity: ${}_nC_r = {}_nC_{n-r}$

$${}_nC_r = {}_{n-1}C_r + {}_{n-1}C_{r-1}$$

$$\sum_{r=0}^n {}_nC_r = 2^n$$

* Playing Cards:



* Axiomatic Probability :

→ $P(E)$ is in accord with ;

(i) $0 \leq P(E) \leq 1$

(ii) $P(S) = 1$

(iii) For mutually exclusive / disjoint events E_1, E_2, \dots, E_n

$$P(\cup E_i) = \sum P(E_i)$$

$$(E_1 \cap E_2 = \emptyset)$$

→ General properties :

(a) $P(E^c) = 1 - P(E)$

(b) $P(\emptyset) = 0$

(c) $P(E_1 \cup E_2) = P(E_1) + P(E_2) - P(E_1 \cap E_2)$

→ Other approaches of probability are ;

- classical / Apriori / Theoretical approach
- Relative frequency / Aposteriori / Empirical approach
- Subjective approach

* Independent Event :

→ Two event E & F are independent if and only if

(i) $P(E \cap F) = P(E) \times P(F)$

→ Three event E, F , & G are independent if and only if

(i) $P(E \cap F \cap G) = P(E) \times P(F) \times P(G)$

(ii) $P(E \cap F) = P(E) \times P(F)$

(iii) $P(F \cap G) = P(F) \times P(G)$

(iv) $P(G \cap E) = P(G) \times P(E)$

→ If E & F are independent, then following are also independent.

(i) E and F^c

(ii) E^c and F

(iii) E^c and F^c

* Conditional Probability :

→ Probability of E conditioned on F :

$$P(E|F) = \frac{P(E \cap F)}{P(F)} ; P(F) > 0$$

→ If E and F are independent then $P(E|F) = P(E)$.

→ Multiplication rule:

$$P(E \cap F) = P(E) \cdot P(F|E)$$

$$P(E_1 \cap E_2 \cap E_3 \cap \dots \cap E_n) = P(E_1) \cdot P(E_2|E_1) \cdot P(E_3|E_1 \cap E_2) \dots P(E_n|E_1 \cap E_2 \dots \cap E_{n-1})$$

* Total Probability :

→ Let's F_1, F_2, \dots, F_k are mutually exclusive and exhaustive then for any event E;

$$P(E) = \sum_{i=1}^k P(E|F_i) \cdot P(F_i)$$

* Bay's Rule :

→ Let's F_1, F_2, \dots, F_k are mutually exclusive and exhaustive then for any event E;

$$P(F_i|E) = \frac{P(E|F_i) \cdot P(F_i)}{\sum_{i=1}^k P(E|F_i) \cdot P(F_i)}$$

* Random Variable :

→ Definition: The quantities of interest or real valued functions defined on the sample space are known as random variable.

→ Discrete random variable

Continuous random variable

* Probability Mass Function (PMF):

→ PMF for discrete random variable defined as;

$$P(x_i) = P(X=x_i) \quad (\text{i.e. probability of occurring } x_i)$$

→ General properties:

$$P(x_i) \geq 0$$

$$\sum_{i=1}^{\infty} P(x_i) = 1$$

* Cumulative Distribution Function (CDF):

→ CDF for discrete random variable defined as;

$$F(a) = P(X \leq a) \quad (\text{where } x_1 < x_2 < \dots < x_n)$$

→ For discrete random variable CDF is step function.

$F(x_1)$	0
$F(x_2)$	$0 + P(x_1)$
$F(x_3)$	$0 + P(x_1) + P(x_2)$
\vdots	
$F(x_n)$	$P(x_1) + P(x_2) + \dots + P(x_{n-1})$
$F(x_{n+1})$	1

* Expectation of Random Variable:

→ Expectation of Random variable x_i where $i=1$ to n is;

$$E(X) = \sum_{i=1}^{\infty} x_i P(x_i)$$

→ It is 'Long run Average' value of random variable.

* Variance of Random Variable:

→ Variance of Random variable x_i where $i=1$ to n is;

$$V(X) = E((X-\mu)^2) \text{ where } \mu = E(X)$$

$$\therefore V(X) = E(X^2) - E(X)^2$$

* Standard Deviation of Random Variable:

→ It is positive square root of variance of random variable.

* Proposition Rules:

$$\rightarrow E(ax+b) = a E(X) + b$$

$$V(ax+b) = a^2 V(X)$$

$$SD(ax+b) = a SD(X)$$

$$\rightarrow E(X) + E(Y) = E(X+Y) \text{ is always true}$$

$$\rightarrow V(X+Y) = V(X) + V(Y) \text{ is only true when } X \text{ \& } Y \text{ are independent.}$$

$$\rightarrow SD(X+Y) = \sqrt{V(X) + V(Y)} \text{ is only true when } X \text{ \& } Y \text{ are independent.}$$

* Bernoulli Random Variable:

→ A random variable that takes either 0 or 1.

X	0	1
$P(X=x_i)$	$1-p$	p

$$E(X) = p$$

$$V(X) = p(1-p)$$

* Uniformly Distributed Random variable:

→ A random variable that takes values 1 to n .

X	1	2	n
$P(X=x_i)$	$\frac{1}{n}$	$\frac{1}{n}$	$\frac{1}{n}$

$$E(X) = \frac{n+1}{2}$$

$$V(X) = \frac{n^2-1}{12}$$

* Hypergeometric Random Variable:

→ Let's there is two category in population of size N . If size of category 1 is m , then size of another category is $N-m$. Choosing a sample of size n is having i from category 1 then;

$$P(X=i) = \frac{\binom{m}{i} \binom{N-m}{n-i}}{\binom{N}{n}}, \quad i=0,1,2,\dots,n$$

Here, X is called hypergeometric random variable.

$$\rightarrow E(X) = \frac{nm}{N}$$

$$V(X) = \frac{nm}{N} \left[\frac{(n-1)(m-1)}{(N-1)} - \frac{nm}{N} + 1 \right]$$

* Binomial Random Variable:

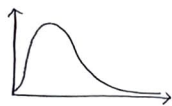
→ Independent and identically distributed (IID) Bernoulli random variables is called Binomial Random variable because its PMF is binomial.

→ Let n Bernoulli trials are performed with probability of success in each trial p . Let X denotes the no. of successes in n trials then;

$$P(X=i) = \binom{n}{i} p^i (1-p)^{n-i} \quad (X \sim B(n,p))$$

* Graph of Binomial Distribution:

(i) $p < 0.5$ and n small.



(iii) $p = 0.5$



(ii) $p > 0.5$ and n small.



(iv) n large.

Approches symmetry.

* Expectation & Variance of Binomial Distribution :

$$\rightarrow E(X) = nP$$

$$V(X) = np(1-p)$$

$$\rightarrow p = 1 - \frac{V(X)}{E(X)} \quad (\text{only for Bernoulli \& Binomial Random variables.})$$

* Straight Line Fit by Min(SSE) :

$$\rightarrow \text{Square Sum Error (SSE)} = \sum (y_i - (mx_i + c))^2$$

$$\rightarrow m = \frac{n \sum x_i y_i - \sum x_i \sum y_i}{n \sum x_i^2 - (\sum x_i)^2}$$

$$c = \bar{y} - m\bar{x}$$