# **Unit 1: Basic Probability**

- 1.  $Probability = P(A) = \frac{No. of possible outcomes}{Total no. of outcomes}$
- 2. Probability of an impossible event =  $P(\phi) = 0$ 
  - $P(\bar{A}) = 1 P(A)$
- 3.  $P(A) + P(\bar{A}) = 1$  $P(A) \le 1$

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

- If A and B are mutually exclusive events (do not occur simultaneously) then  $P(A \cap B) = 0 :: P(A \cup B) = P(A) + P(B)$
- If A and independent events then  $P(A \cap B) = P(A) P(B)$

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

- If A, B and C are mutually exclusive events (do not occur simultaneously) then  $P(A \cap B) = 0$ ,  $P(B \cap C) = 0$ ,  $P(A \cap B) = 0$  and  $P(A \cap B \cap C) = 0$
- If A and independent events then  $P(A \cap B \cap C) = P(A) P(B) P(C)$

4.

$$P(\bar{A} \cap B) = P(B) - P(A \cap B)$$
  
 
$$P(A \cap \bar{B}) = P(A) - P(A \cap B)$$

#### De Morgan's Laws:

$$P(\overline{A \cap B}) = P(\overline{A} \cup \overline{B})$$
  
$$P(\overline{A \cup B}) = P(\overline{A} \cap \overline{B})$$

$$P(A \cup B) = 1 - P(\bar{A} \cap \bar{B})$$

$$P(A \cap B) = 1 - P(\bar{A} \cup \bar{B})$$

# ${\it Conditional\ Probability}:$

5. 
$$P(A/B) = \frac{P(A \cap B)}{P(B)} \therefore P(A \cap B) = P(A/B) P(B)$$
$$P(B/A) = \frac{P(A \cap B)}{P(A)} \therefore P(A \cap B) = P(B/A) P(A)$$

#### Bayes' Theorem:

 $A_1, A_2, ... A_n$  are mutually exclusive and exhaustive events and B is an event that occur in combination with any one of the events  $A_1, A_2, ... A_n$  then

$$P(A_i/B) = \frac{P(A_i)P(B/A_i)}{\sum_{i=1}^n P(A_i)P(B/A_i)}$$

 ${\it Properties of Probability \, Mass \, Function \, (One \, Dimensional \, Discrete):}$ 

$$p(x_i) \ge 0$$
 for all values of i

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

# Properties of Probability Density Function (One Dimensional Continuous):

$$f(x) \ge 0 - \infty < x < \infty$$

8. 
$$\int_{-\infty}^{\infty} f(x) dx = 1$$

9.

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

### Properties of Joint Probability Mass Function (Two Dimensional Discrete):

 $p_{XY}(x_i, y_i) \ge 0$  for all values of i and j

$$\sum_{j=1}^{n} \sum_{i=1}^{m} p_{XY}(x_i, y_j) = 1$$

Marginal Probability 
$$p_X(x_i) = \sum_{i=1}^{m} p(x_i, y_j)$$

Marginal Probability  $p_Y(y_i) = \sum_{i=1}^{n} p(x_i, y_j)$ 

Conditional Probability 
$$p_{X/Y} = P(X = x/Y = y) = \frac{P(X = x, Y = y)}{P(Y = y)}$$

Conditional Probability 
$$p_{Y/X} = P(Y = y/X = x) = \frac{P(X = x, Y = y)}{P(X = x)}$$

Necessary and sufficient condition for X and Y to be independent is  $P(X = x_i, Y = y_i) = P(X = x_i)P(Y = y_j)$ 

# Properties of Joint Probability Density Function (Two Dimensional Continuous):

$$f(x,y) \ge 0$$
 for all  $x, y$   
$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) dx dy = 1$$

$$P(a \le X \le b, c \le Y \le d) = \int_{c}^{d} \int_{a}^{b} f(x, y) dx dy$$

Marginal Probability 
$$f_X(x) = \int_{-\infty}^{\infty} f(x, y) dy$$

Marginal Probability  $f_Y(y) = \int_{-\infty}^{\infty} f(x, y) dx$ 

Conditional Probability 
$$f(x/y) = \frac{f(x,y)}{f_{Y(y)}}$$

Conditional Probability 
$$f(y/x) = \frac{f(x,y)}{f_{x(x)}}$$

*Necessary* and sufficient condition for *X* and *Y* to be independent is  $f(x,y) = f_X(x) f_Y(y)$ 

# **Unit 2: Some Special Probability Distributions**

#### **Binomial Distribution:**

$$P(X = x) = nCx p^{x} q^{n-x}, x = 0, 1, 2, ..., n$$

n = no. of trials

p = probability of success

1. 
$$q = 1 - p = probability of failure$$

mean = np

variance = npq

 $SD = \sqrt{npq}$ 

#### Poisson Distribution:

Used when n is very large and p is very small.

$$P(X = x) = \frac{e^{-\lambda} \lambda^x}{x!}, x = 0, 1, 2, ..., n$$

2.  $\lambda = np$ 

 $mean = np = \lambda$ 

 $variance = \lambda$ 

 $SD = \sqrt{\lambda}$ 

#### Normal Distribution:

Take a new random variable  $Z = \frac{X - \mu}{\sigma}$ 3.

then use Z – table to find probability

# **Exponential Distribution**:

$$f(x) = \lambda e^{-\lambda x}, x > 0$$

 $mean = \frac{1}{\lambda}$ 

 $variance = \frac{1}{\lambda^2}$ 

#### Gamma Distribution:

$$f(x) = \frac{\lambda^r}{\Gamma r} x^{r-1} e^{-\lambda x}, x > 0$$

5. 
$$mean = \frac{r}{\lambda}$$

 $variance = \frac{r}{\lambda^2}$ 

 $SD = \frac{\sqrt{r}}{\lambda}$ 

#### **Unit 3: Basic Statistics**

Note: If data is given in the form of class then  $x_i = middle \ value \ of \ class$ 

Arithmetic Mean  $\bar{x}$  or  $\mu = \frac{\sum_{i=1}^{n} x_i}{n}$ 

 $\rightarrow$  when frequency is given, **Weighted Arithmetic Mean**  $\bar{x}$  or  $\mu = \frac{\sum_{i=1}^{n} f_i x_i}{\sum_{i=1}^{n} f_i}$ 

**Expectation**  $E(X) = Mean = \sum_{i=1}^{\infty} x_i p(x_i)$ 

→ Important Results:

$$E(X+k) = E(X) + k$$

$$E(aX \pm b) = aE(X) \pm b$$

$$E(X + Y) = E(X) + E(Y)$$

E(XY) = E(X)E(Y) if X and Y are independent random variables.

For median first arrange observations in ascending order.

 $\rightarrow$  If no. of observations = n = odd

**Median** 
$$M = \left(\frac{n+1}{2}\right)^{th}$$
 observation

 $\rightarrow$  If no. of observations = n = even

Median 
$$M = \frac{\left(\frac{n}{2}\right)^{th} observation + \left(\frac{n}{2} + 1\right)^{th} observation}{2}$$

2.

1.

$$\rightarrow$$
 when frequency is given, **Weighted Median**  $M = l + \frac{\binom{N}{2} - m}{f} \times c$ 

 $l = lower \ limit \ of \ median \ class$ 

m = cumulative frequency upto median class

 $f = frequency \ of \ median \ class$ 

 $c = class\ length\ of\ median\ class$ 

Median class is a class corresponding to cumulative frequency which is lowest greater than or equal to  $\frac{N}{2}$ .

 $\textit{Mode}\ Z = \textit{Observation}\ \textit{which occurs maximum time}.$ 

$$\rightarrow$$
 when frequency is given, **Weighted Mode**  $Z = l + \frac{f_1 - f_0}{2f_1 - f_0 - f_2} \times c$ 

 $l = lower \ limit \ of \ modal \ class$ 

 $f_1 = frequency of modal class$ 

 $f_0 = f$ requency of class just above modal class

 $f_2 = frequency \ of \ class \ just \ below \ modal \ class$ 

 $c = class\ length\ of\ modal\ class$ 

Modal class is a class with highest frequency.

| 4. | Standard deviation $\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{N}}$ $\rightarrow \text{ when frequency is given, Standard deviation } \sigma = \sqrt{\frac{\sum_{i=1}^{n}f_i(x_i - \bar{x})^2}{\sum_{i=1}^{n}f_i}}$ Standard deviation $\sigma = \sqrt{E(X^2) - [E(X)]^2}$   |  |  |  |  |
|----|---|--|--|--|--|
| 5. | Variance is square of standard deviation.  Variance $\sigma^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{N}$ $\rightarrow$ when frequency is given, Variance $\sigma^2 = \frac{\sum_{i=1}^n f_i (x_i - \bar{x})^2}{\sum_{i=1}^n f_i}$ Variance $V(X) = \sigma^2 = E(X^2) - [E(X)]^2$ $\rightarrow$ Important Results: $V(X + k) = V(X)$ $V(aX \pm b) = a^2V(X)$ $V(k) = 0$ $V(kX) = k^2V(X)$ |  |  |  |  |
| 6. |   |  |  |  |  |
| 7. |   |  |  |  |  |
| 8. | Karl Pearson's Coefficient of Skewness $S_k = \frac{Mean - Mode}{Standard\ Deviation}$<br>If the mode is ill-defined then $S_k = \frac{3(Mean - Median)}{Standard\ Deviation}$  |  |  |  |  |

 $S_k$  lies betwen -1 and 1. For a positively skewed distribution,  $S_k > 0$ 

For a negatively skewed distribution,  $S_k < 0$ For a symmetrical distribution,  $S_k = 0$ 

Skewness 
$$\beta_1 = \frac{\mu_3^2}{\mu_2^3}$$

For a positively skewed distribution,  $\mu_3 > 0$ For a negatively skewed distribution,  $\mu_3 < 0$ For a symmetrical distribution,  $\mu_3 = 0$ 

Kurtosis  $\beta_2 = \frac{\mu_4}{\mu^2}$ 

9. For a Leptokurtic,  $\beta_2 > 3$ 

For a Platykurtic,  $\beta_2 < 3$ 

For a Mesokurtic,  $\beta_2 = 3$ 

Correlation:

 $\textit{Karl Pearson's Correlation Coefficient } r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$ 

10. Spearman's Rank Correlation Coefficient  $r = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2 - 1)}$ 

d = Difference between ranks R<sub>1</sub> and R<sub>2</sub> given by two judges N = No.of pairs (contestants)

Regression:

Method of least squares:

 $\rightarrow$  y = ax + b (Regression line of y on x)

$$\sum y = a \sum x + nb$$
  
 
$$\sum xy = a \sum x^2 + b \sum x$$

$$\sum x = a \sum y + nb$$

$$\sum xy = a\sum y^2 + b\sum y$$

11. Regression Coefficients:  

$$b_{yx} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$$

$$b_{xy} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

**Regression line of y on x**:  $y - \bar{y} = b_{vx}(x - \bar{x})$ 

**Regression line of x on y**:  $x - \bar{x} = b_{xy}(y - \bar{y})$ 

Correlation coefficient  $r = \int b_{xy} \times b_{yx}$ 

If  $b_{xy} > 0$ ,  $b_{yx} > 0$  then r > 0 and if  $b_{xy} < 0$ ,  $b_{yx} < 0$  then r < 0

# **Unit 4: Applied Statistics: Test of Hypothesis**

#### Large Samples: n > 30

|    | Critical Value $Z_{\alpha}$ | Level of Significance $(\alpha)$ |                        |                        |
|----|-----------------------------|----------------------------------|------------------------|------------------------|
| 1. |                             | 1%                               | 5%                     | 10%                    |
|    | Two tailed test             | $ Z_{\alpha}  = 2.58$            | $ Z_{\alpha}  = 1.96$  | $ Z_{\alpha}  = 1.645$ |
|    | Right/Left tailed test      | $ Z_{\alpha}  = 2.33$            | $ Z_{\alpha}  = 1.645$ | $ Z_{\alpha}  = 1.28$  |

# Test of Significance for Single Proportion

$$Z = \frac{p - P}{\sqrt{\frac{PQ}{n}}}$$

p = Sample Proportion

n = Sample size

P = Total population proportion

Q = 1 - P

2. when P and Q are not known, p and q are used.

#### Confidence limits:

95% confidence limits = 
$$p \pm 1.96 \sqrt{\frac{PQ}{n}}$$
  
99% confidence limits =  $p \pm 2.58 \sqrt{\frac{PQ}{n}}$ 

# Test of Significance for Difference of Proportions

$$Z = \frac{P_1 - P_2}{\sqrt{\frac{P_1 Q_1}{n_1} + \frac{P_2 Q_2}{n_2}}}$$

when  $P_1$  and  $P_2$  are not known,  $p_1$ ,  $p_2$ ,  $q_1$  and  $q_2$  are used.

#### 3. **Confidence limits**:

95% confidence limits = 
$$(p_1 - p_2) \pm 1.96 \sqrt{\frac{P_1 Q_1}{n_1} + \frac{P_2 Q_2}{n_2}}$$
  
99% confidence limits =  $(p_1 - p_2) \pm 2.58 \sqrt{\frac{P_1 Q_1}{n_1} + \frac{P_2 Q_2}{n_2}}$ 

# Test of Significance for Single Mean

When Standard deviation of population  $\sigma$  is not known

$$Z = \frac{\bar{x} - \mu}{\left(\frac{s}{\sqrt{n}}\right)}$$

s = sample standard deviation

#### Confidence limits:

95% confidence limits =  $\bar{x} \pm 1.96 \left(\frac{\sigma}{\sqrt{n}}\right)$ 

99% confidence limits =  $\bar{x} \pm 2.58 \left( \frac{\delta}{\sqrt{n}} \right)$ 

# Test of Significance for Difference of Means

$$Z = \frac{\frac{1}{x_1} - \frac{3}{x_2}}{\sqrt{\left(\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}\right)}}$$

When Standard deviations of population  $\sigma_1$  and  $\sigma_2$  are not known  $Z = \frac{\overline{x_1 - \overline{x_2}}}{\sqrt{\left(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right)}}$ 

$$Z = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)}}$$

# Confidence limits:

95% confidence limits =  $(\overline{x_1} - \overline{x_2}) \pm 1.96 \sqrt{\left(\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}\right)}$ 

99% confidence limits =  $(\overline{x_1} - \overline{x_2}) \pm 2.58 \sqrt{\left(\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}\right)}$ 

# Test of Significance for Difference of S.D. $Z = \frac{S_1 - S_2}{\sqrt{\frac{S_1 - S_2}{S_1 - S_2}}}$

$$Z = \frac{s_1 - s_2}{\sqrt{\left(\frac{\sigma_1^2}{2n_1} + \frac{\sigma_2^2}{2n_2}\right)}}$$

When Standard deviations of population  $\sigma_1$  and  $\sigma_2$  are not known  $Z = \frac{s_1 - s_2}{\sqrt{\left(\frac{s_1^2}{2n_1} + \frac{s_2^2}{2n_2}\right)}}$ 

$$Z = \frac{s_1 - s_2}{\sqrt{\left(\frac{s_1^2}{2n_1} + \frac{s_2^2}{2n_2}\right)}}$$

# *Small Samples*: $n \leq 30$

# $t-Test: Test\ of\ Significance\ for\ Single\ Mean$

7. 
$$t = \frac{\bar{x} - \mu}{\left(\frac{s}{\sqrt{n-1}}\right)} \text{ where } s = \sqrt{\frac{\sum (x-\bar{x})^2}{n}} \text{ with degree of freedom (df) } v = n-1$$

#### Confidence limits:

95% confidence limits = 
$$\bar{x} \pm t_{0.05} \left( \frac{s}{\sqrt{n-1}} \right)$$
  
99% confidence limits =  $\bar{x} \pm t_{0.01} \left( \frac{s}{\sqrt{n-1}} \right)$ 

# t – Test: Test of Significance for Difference of Means

$$t = \frac{\bar{x} - \bar{y}}{s\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \text{ where } s = \sqrt{\frac{\sum (x - \bar{x})^2 + \sum (y - \bar{y})^2}{n_1 + n_2 - 2}} \text{ or } s = \sqrt{\frac{n_1 s_1^2 + n_2 s_2^2}{n_1 + n_2 - 2}}$$

with degree of freedom (df)  $v = n_1 + n_2 - 2$ 

#### Confidence limits:

95% confidence limits = 
$$(\bar{x} - \bar{y}) \pm t_{0.05} \left( \frac{1}{s\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \right)$$

99% confidence limits = 
$$(\bar{x} - \bar{y}) \pm t_{0.01} \left( \frac{1}{s\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \right)$$

# t-Test: Test of Significance for Correlation Coefficients

# 

# Snedecor's F-Test for Ratio of Variances

$$F = \frac{S_1^2}{S_2^2}$$
 where  $S_1^2 > S_2^2$ 

10. 
$$S_1^2 = \frac{\sum (x - \bar{x})^2}{n_1 - 1}$$
 and  $S_2^2 = \frac{\sum (y - \bar{y})^2}{n_2 - 1}$ 

10.  $S_1^2 = \frac{\sum (x - \bar{x})^2}{n_1 - 1} \text{ and } S_2^2 = \frac{\sum (y - \bar{y})^2}{n_2 - 1}$  with numerator df  $v_1 = n_1 - 1$  and denominator df  $v_2 = n_2 - 1$ 

if  $s_1$  and  $s_2$  (Sample SD) are given then  $S_1^2 = \frac{n_1 s_1^2}{n_1 - 1}$  and  $S_2^2 = \frac{n_2 s_2^2}{n_2 - 1}$ 

#### Chi - Square Test: Goodness of Fit

$$\chi^2 = \sum \frac{(f_o - f_e)^2}{f_e}$$
 with degree of freedom (df)  $v = n - 1$ 

# 11. Chi – Square Test for Independece of Attributes

$$\chi^{2} = \sum \frac{(f_{o} - f_{e})^{2}}{f_{e}} \text{ with } df \text{ } v = (no. \text{ of rows} - 1)(no. \text{ of colums} - 1)$$

$$f_{e} = \frac{(Row \text{ total}) \times (Column \text{ total})}{Total \text{ } frequency} = \frac{(A_{i})(B_{j})}{N}$$

# **Unit 5: Curve Fitting by Numerical Method**

#### Linear Approximation:

- Equations for the best fitting straight line y = a + bx $\Sigma xy = a\Sigma x + b\Sigma x^2$
- 1.  $\Sigma y = na + b\Sigma x$ 
  - Equations for the best fitting straight line y = ax + b  $\Sigma xy = b\Sigma x + a\Sigma x^2$  $\Sigma v = nb + a\Sigma x$

#### Least Square Approximation:

- Equations for the best fitting parabola of second degree  $\mathbf{y} = \mathbf{a}\mathbf{x}^2 + \mathbf{b}\mathbf{x} + \mathbf{c}$   $\Sigma x^2 y = a\Sigma x^4 + b\Sigma x^3 + c\Sigma x^2$   $\Sigma xy = a\Sigma x^3 + b\Sigma x^2 + c\Sigma x$  $\Sigma \mathbf{v} = a\Sigma x^2 + b\Sigma x + nc$
- Equations for the best fitting parabola of second degree  $\mathbf{y} = \mathbf{a} + \mathbf{b}\mathbf{x} + \mathbf{c}\mathbf{x}^2$   $\Sigma x^2 y = c\Sigma x^4 + b\Sigma x^3 + a\Sigma x^2$   $\Sigma xy = c\Sigma x^3 + b\Sigma x^2 + a\Sigma x$  $\Sigma y = c\Sigma x^2 + b\Sigma x + na$

#### Non-polynomial Approximation OR Non-linear Regression

 $y = ae^{bx}$  yields

2.

3.

- Taking Logarithm on both sides log y = log a + bx
  - Denoting  $\log y = Y$  and  $\log a = A$ , the above equation becomes
- Y = A + bx which is a straight line.
- From above equation A, b can be found & consequently a = Antilog A can be calculated.

#### $y = ax^b$ yields

- Taking Logarithm on both sides log y = log a + b log x
- Denoting  $\log y = Y$ ,  $\log a = A$  and  $\log x = X$  the above equation becomes
- Y = A + bX which is a straight line.
- From above equation A, b can be found & consequently a = Antilog A can be calculated.

 $y = ab^x yields$ 

- Taking Logarithm on both sides  $\log y = \log a + x \log b$
- Denoting log y = Y, log a = A and log b = B the above equation becomes
- Y = A + Bx which is a straight line.
- From above equation A, B can be found & consequently a = Antilog A and b = Antilog B can be calculated.