| 5.N. | STATISTIC | FORMULA | STATEMENTS |
|------|----------------------------------|---|--|
| 1. | Mean | | |
| (a) | Population Mean (µ) | $\frac{\sum_{i=1}^{n} x_i}{N}$ | |
| | | OR | The mean is the most widely spread measure of central tendency. It is the simple average |
| | | $\frac{x_1 + x_2 + x_3 + \dots + x_{N-1} + x_n}{N}$ | of the dataset. |
| | | (Where, N=size of population) | |
| (b) | Sample Mean (\bar{x}) | $\frac{\sum_{i=1}^{n} x_i}{n}$ | |
| | | (Where, n=size of sample) | |
| 2. | Median (M) | if n is odd, $\left(\frac{n+1}{2}\right)^{th}$ | The median is the midpoint of the ordered dataset. |
| | | if n is even, $\frac{\left(\frac{n}{2}\right)^{th} + \left(\frac{n}{2} + 1\right)^{th}}{2}$ | |
| 3. | Mode | | The mode is the value that occurs most often. A dataset can have 0 modes, 1 mode or multiple modes. |
| 4. | Skewness | $\frac{\frac{1}{n}\sum_{i=1}^{n}(x_{i}-\overline{x})^{3}}{\sqrt[3]{\frac{1}{n-1}\sum_{i=1}^{n}(x_{i}-\overline{x})^{2}}}$ | Skewness indicates whether the data is concentrated on one side or not. |
| (a) | Positive skewness | Mean > Median & Mode | If the data is |
| (b) | Negative skewness | Mode > Median & Mean | Right concentrated = Positive skewness |
| (c) | Zero skewness | Mean = Median = Mode | Left concentrated = Negative skewness No concentrated = Zero skewness |
| 5 | Variance | | |
| (a) | Population Variance (σ^2) | $\frac{\sum_{i=1}^{n}(x_{i}-\mu)^{2}}{N}$ (Where, μ =mean of population) | Variance measures the dispersion of a set of data points around their mean. |
| (b) | Sample Variance (s²) | $\frac{\sum_{i=1}^{n}(x_{i}-\overline{x}))^{2}}{n-1}$ (Where, \overline{x} =mean of sample) | |

| 6. | Standard Deviation | | |
|-----|-----------------------------------|---|--|
| (a) | Population Standard Deviation (σ) | $\sqrt{\sigma^2}$ | Standard deviation is the most common |
| (b) | Sample Standard Deviation (s) | $\sqrt{s^2}$ | Standard deviation is the most common measure of variability for a single Dataset. |
| 7. | Coefficient of Variance (Cv) | Standard Deviation Mean | Cv is the most common measure of variability for two or more dataset. |
| 8. | Covariance | | |
| (a) | Sample Formula | $S_{xy} = \frac{\sum_{i=1}^{n} (x_i - \bar{x}) * (y_i - \bar{y})}{n - 1}$ | The two variables are correlated and the main statistic to measure this correlation is called covariance. |
| (b) | Population Formula | $\sigma_{xy} = \frac{\sum_{i=1}^{N} (x_i - \mu_x) * (y_i - \mu_y)}{N}$ | Covariance can take on values from -∞ to +∞. |
| 9. | Correlation coefficient | $\frac{Cov(x,y)}{Stdev(x)*Stdev(y)}$ | Correlation adjusts covariance, so that the relationship between the two variables becomes easy and intuitive to interpret. Correlation coefficient is between Correlation of 1 (perfect positive corelation) Correlation of 0 (variables are independent) Correlation of -1 (perfect negative corelation) |

| 10. | Probability distribu | tion | Distribution is a function that shows the |
|-----|---|---|---|
| | obability distribu | | possible values for a variable and how often |
| | | | they occur. |
| (a) | Normal distribution | $N \sim (\mu , \sigma^2)$ | |
| (b) | Standard normal distribution | $N \sim (0,1)$ | The Standard Normal distribution is a particular case of the Normal distribution. It has a mean of 0 and a standard deviation of 1. |
| (c) | Z-score | $\frac{x-\mu}{\sigma}$ | Variable which converts normal distribution variable to standard normal distribution is called z-score. |
| 11. | Confidence interval | s | |
| (a) | Confidence Level | $(1-\alpha)$ $0 \le \alpha \le 1$ | |
| (b) | Margin of Error (ME) | reliability factor * $\frac{\sigma}{\sqrt{n}}$ | |
| | | or $reliability\ factor*rac{s}{\sqrt{n}}$ | A confidence interval is an interval within |
| (c) | Standard Error | $rac{\sigma}{\sqrt{n}}$ or $rac{S}{\sqrt{n}}$ | which we are confident (with a certain percentage of confidence) the population parameter will fall. |
| (d) | Population variance known (Z) | $ \bar{x} \pm z_{\alpha/2} \frac{\sigma}{\sqrt{n}} $ | General formula of Confidence Interval: $C.I. = [\overline{x} \pm ME]$ Where ME is the margin of error. |
| (e) | Population variance unknown (T) | $\bar{x} \pm t_{n-1,\alpha/2} \frac{s}{\sqrt{n}}$ | |
| (f) | For two population means with dependent | $\bar{d} \pm t_{n-1,\alpha/2} \frac{s_d}{\sqrt{n}}$ | |
| (g) | Student's T distribution | $t_{n-1,\alpha} = \frac{\bar{x} - \mu}{s / \sqrt{n}}$ | |

| 12. | Hypothesis Testing | 1 | |
|-----|--------------------------------|--|---|
| (a) | TYPE I ERROR | REJECTING TRUE NULL HYPOTHESIS OR FALSE POSITIVE | A hypothesis is an idea that can be tested NULL HYPOTHESIS \rightarrow (H_o) |
| (b) | TYPE II ERROR | ACCEPTING A FALSE NULL HYPOTHESIS OR FALSE NEGETIVE | ALTERNATIVE HYPOTHESIS \rightarrow (H_1 OR H_A) |
| (c) | P value | P-value is the smallest level of significance at which we can still reject the null hypothesis, given the observed sample statistic. | |
| 13. | Advance Statistics | | |
| (a) | Linear Regression | $\widehat{y} = b_0 + b_1 x_1$ Where, $\widehat{y} = Predicted / inferred value$ $b_0 = Intercept$ | (SST = SSR + SSE) |
| (b) | Sum of squares total | $\sum_{i=1}^{n} (y_i - \bar{y})^2$ | SSE SSR SST |
| (c) | Sum of squares regression | $\boxed{\sum_{i=1}^n (\widehat{y_i} - \bar{y})^2}$ | · · · · · · · · · · · · · · · · · · · |
| (d) | Sum of squares error | $\sum_{i=1}^n e_i^2$ | OLS \rightarrow Ordinary least squares OLS stands for min SSE Or we can say that lower error. $\min \sum_{i=1}^{n} e_i^2$ |
| (e) | R-Square | $\frac{SSR}{SST}$ | ∠ -1 t |
| (f) | Multivariate linear regression | $\widehat{y} = b_0 + b_1 x_1 + b_2 x_2 + \dots + b_k x_k$ | when we have multiple variables then we use multivariate analysis. |
| (g) | Adjusted R- Square | $\overline{R^2} < R^2$ | The adjusted R-squared penalizes excessive use of variables. adjusted R square always use in multilinear regression. |

| 14. | Principle Componen | t Analysis (PCA) | |
|-----|--|--|---|
| (a) | Covariance of X&Y | $cov(x,y) = \sum_{i=1}^{n} \frac{(x_i - \bar{x})(y_i - \bar{y})}{n-1}$ | The objective of PCA is to reduce the dimensionality of the data while retaining as much of the variation in the original dataset as |
| (b) | Identical Matrix | $\sum_{i=1}^{n-1} n-1$ $C-\lambda I=0$ | possible. |
| | | | |
| 15. | Slope (m) | $m = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sum (x - \bar{x})^2}$ | Y = mx+c (equation of regression line) Where m=slope |
| | | $\sum_{x} (x-x)^2$ | The slope indicates the steepness of a line. |
| 16. | CHI-SQUARE TEST (x2) | $x^2 = \frac{\sum (O_i - E_i)^2}{E_i}$ | The Chi-Square test is a statistical procedure for determining the difference between observed and expected data. This test can also be used to determine whether it correlates to the categorical variables in our data. |
| 17. | Gradient Descent | | Gradient descent is an algorithm that finds the best fit line for given training data set. |
| (a) | Mean squared error/ Cost function/ OLS | $\frac{1}{n}\sum_{i=1}^{n}\left(y_{i}-(mx_{i}+b)\right)^{2}$ | The Mean Squared Error measures how close a regression line is to a set of data points. |
| 18. | Polynomial Regression | $y = b_0 + b_1 x_1 + b_2 x_1^2 + \dots + b_n x_1^n$ | Polynomial regression is a type of regression analysis in which the relationship between the independent variable (x) and the dependent variable (y) is modelled as an nth degree polynomial. |
| | | | $y = b_0 + b_1 x_1 + b_2 x_1^2$ |

| 19. | Bias & Variance | | Bias refers to the Training Data |
|-----|---|--|---|
| (a) | Total error | Bias²+Variance+Irreducible error | Variance refers to the Testing data. Low bias, High variance overfitting problem High bias, Low variance underfitting problem Low bias, Low variance = Good Model |
| 20. | Simple Vector Regi | ression (SVR) | |
| (a) | Hyperplane equation | Y=wx+b | Decision Boundary |
| (b) | Decision boundary | wx+b=a (for positiove side) wx+b=-a (for negative side) | Boundary |
| (c) | Hyperplane satisfy SVR | -a < Y- wx+b < +a | Main aim in SVR is to decide a decision boundary at 'a' distance from the original hyperplane such that data points closest to the hyperplane or the support vectors are within that boundary line. |
| 21. | Regularization | | Regularization is a technique used in machine learning to prevent overfitting and improve the generalization ability of a model. |
| (a) | Lasso Regression (L1 regularization) | Loss + α w w = w_1 + w_2 + w_3 ++ w_n | Scaled down to 0 (due to we are eliminate the feature) this also called as FEATURE ELIMINATION TECHNIQEU |
| (b) | Ridge Regression (L2 regularization) | Loss + $\alpha \mathbf{w} ^2$ $ \mathbf{w} ^2 = w_1^2 + w_2^2 + w_3^2 + + w_n^2$ | Scaled down high coefficient to low coefficient but it not 0 (scale down never happened to 0). |
| (c) | Elastic net Regression | Loss + $\alpha_1 \mathbf{w} + \alpha_2 \mathbf{w} ^2$ | It uses the penalties from both the lasso and ridge techniques to regularize regression models |

| 22. | Feature Scaling | | Feature scaling is a data preprocessing technique that is used to bring different |
|-----|------------------------|--|---|
| (a) | Normalization | $X' = \frac{X - X_{min}}{X_{max} - X_{min}}$ | features of a dataset onto a similar scale. Normalization typically refers to scaling a set of values to a range between 0 and 1. This is useful when the range of the data varies widely, as it puts all the values on a similar scale. |
| (b) | Standardization | $X^{'} = \frac{X - \mu}{\sigma}$ | Standardization involves transforming a set of values to have a mean of 0 and a standard deviation of 1. This is useful when the distribution of the data is normal or approximately normal. |
| 23. | Confusion Metrix | | |
| (a) | Model Accuracy | $\frac{TP + TN}{TOTAL}$ | It is a matrix that compares the predicted labels of a model with the actual labels in the |
| (b) | Error Rate | 1-Accuracy | test dataset, and provides a summary of the model's performance |
| | | Or | |
| | | $\frac{FP + FN}{TOTAL}$ | Actual Values |
| (c) | Recall | TP Actual Yes | Positive (1) Negative (0) |
| | | Or | Positive (1) TP FP |
| | | $\frac{TP}{TP + FN}$ | Predicted (0) LN LN |
| (d) | Precision | TP Predicted Yes | |
| (e) | F1 score | $\frac{2.(Precission * Recall)}{((Precission + Recall)}$ | |
| 24. | Logistic Regression | $\max \sum_{i=1}^{n} y_i w_i^T x_i$ | It is a statistical method for analysing a dataset in which there are one or more independent variable that determine an outcome. Logistic regression also called as logit or maxent |

| 05 | 61 115 11 | | |
|-----|-----------------------|---|---|
| 25. | Sigmoid Function | $P = \frac{1}{1 + e^{-y}}$ $\ln\left(\frac{p}{1 - p}\right) = b_0 + b_{1^*}x$ | When the data has outlier then logistic regression algorithm would misclassify, that's why we use probability concept using the help probability function which is called (SIGMOID FUNCTION). |
| 26. | Support Vector Ma | chines (SVM) | It is a supervised machine learning problem where we try to find a hyperplane that best |
| (a) | For Linear SVM | $\max(\mathbf{w}^*, \mathbf{b}^*) \frac{2}{\ \mathbf{w}\ }$ | separates the two classes. Maximum Margin Positive Hyperplane |
| (b) | For Non-Linear SVM | $\min\left(\mathbf{w}^*, \mathbf{b}^*\right) \frac{\ \mathbf{w}\ }{2} + c \sum_{i=1}^n \zeta_i$ | Maximum Margin Hyperplane Support Vectors X1 |
| | | | Two type of support vector machine -> 1-Linear SVM => When the data is perfectly linearly separable only then we can use Linear SVM. 2-Non-Linear SVM=> if a dataset cannot be classified by using a straight line, then such data is termed as non-linear data |
| 27. | K-Nearest Neighbo | or (KNN) | K-NN algorithm assumes the similarity between the new case/data and available cases |
| (a) | Euclidean distance | $d = \sqrt{\left(x_2 - x_1 ight)^2 + \left(y_2 - y_1 ight)^2}$ | and put the new case into the category that is most similar to the available categories X2 Refore K-NN After K-NN |
| (b) | Manhatten distance | distance = absolute sum xi-yi | Category B New data point assigned to Category A Category A X1 |

| 28. | Naïsa Davas | | The idea of the control of the contr |
|-----|------------------|--|--|
| 20. | Naïve Bayes | | It is a supervised machine learning algorithm, which is used for classification tasks, like text |
| (a) | BERNOULLI | | classification. |
| (a) | NAVE BAYE'S | $P(x=x) = p^x \cdot (1-p)^{1-x}$ | |
| | VARIANCE | $\Gamma(x-x)=p^{-1}(1-p)$ | |
| | | | |
| (b) | GAUSSION | 1 -1 | |
| | NAVE BAYE'S | $f_{(x)} = \frac{1}{\sqrt{2\Pi}\sigma} e^{\frac{-1}{2\sigma^2}} (x - \mu)^2$ | |
| | VARIANCE | √2Πσ 20- | |
| | | $-\infty < x < \infty$ | |
| | | | |
| (c) | MULTINOMIAL | | |
| | NAVE BAYE'S | $P(x_1 = x_i \dots x_k)$ | |
| | VARIANCE | $\frac{n!}{x_1! \dots x_k!} P^{1^{x_1} \dots P_k^{x_k}}$ | |
| | | $P^{1x_1}P_k^{x_k}$ | |
| | | $x_1: x_k$ | |
| (d) | Conditional | $P(A B) = \frac{P(A \cap B)}{P(B)}$ | Conditional probability is a measure of the |
| | Probability | $P(A B) - \frac{P(B)}{P(B)}$ | probability of an event occurring, given that |
| | · · | | another event has already occurred. |
| (e) | Baye's Theorem | $P(A B) = \frac{P(B A) * P(A)}{P(B)}$ | Bayes' Theorem states that the conditional |
| | | P(B) | probability of an event, based on the |
| | | 0(410) 0 | occurrence of another event, is equal to the |
| | | P(A B)=Posterior probability | likelihood of the second event given the first event multiplied by the probability of the first |
| | | P(B A) = Likelihood P(A) =Prior Probability | event. |
| | | P(B) = Marginal likelihood | CVCIII. |
| 29. | Decision Tree | | It is a tree-structured classifier where internal |
| | | | nodes represent the features of a dataset, |
| (a) | Information Gain | $-\frac{P}{P+N}\log_2(\frac{P}{P+N})-\frac{N}{P+N}\log_2(\frac{N}{P+N})$ | branches represent the decision rules and each |
| | | $p+N \log_2(p+N) p+N \log_2(p+N)$ | leaf node represents the outcome. |
| (b) | Entropy | | Decision Node → Root Node |
| | E(A) | $\sum_{i=1}^{\nu} P_{i-1} N_{i}$ | |
| | | $\sum \frac{P_i + N_i}{p + N} (P_i N_i)$ | |
| | | $\sum_{i=1}^{p+N}$ | Sub-Tree Decision Node Decision Node |
| | | | |
| (c) | Gain | I.G E(A) | Leaf Node Leaf Node Decision Node |
| | | | |
| | | | * |
| | | | Leaf Node Leaf Node |
| | | | |

| (d) | GINI Index | $I_G = 1 - \sum_{j=1}^{c} p_j^2$ | |
|-----|--|--|---|
| (e) | Entropy | $I_H = -\sum_{j=1}^c p_j log_2(p_j)$ | |
| 30. | Ensemble Technique | 2 | Ensemble methods is a machine learning technique that combines several base models in |
| (A) | ADABOOST | | order to produce one optimal predictive model. |
| (a) | Performance of Stump | $\frac{1}{2} \log_e (\frac{1 - Total \ Error}{Total \ Error})$ | Ensemble Method is split into three types - 1. Bagging> Random Forest 2. Boosting> (a) ADABOOST |
| (b) | New sample weight | old weight * $e^{\pm Amount\ of\ say\ (\alpha)}$ | (b) GRADIENT BOSSTING (c) XGBOOST 3. Voting (stacking) |
| (B) | Gradient Boosting | | |
| (a) | F(x) | $h_0(x) + l_1 h_1(x) + l_2 h_2(x) + \cdots + l_n h_n(x)$ | |
| | | Where , l = learning rate | |
| 31. | AUC & ROC Curve | | It will visualization for confusion matrix (classification) |
| (a) | True positive rate (TPR) Or Sensitivity | $\left rac{TP}{TP+FN} ight $ | AUC & ROC is graph to measure the accuracy of the dataset |
| (b) | False positive rate (FPR) Or Specificity | $\frac{FP}{FP+TN}$ | TPR AOC |

| 32. | Clustering | | Clustering is an unsupervised machine learning method of identifying and grouping similar data points in larger datasets without concern for the specific outcome. |
|-----|---|---|---|
| | | | Clustering (sometimes called cluster analysis) is usually used to classify data into structures that are more easily understood and manipulated. |
| (a) | Euclidean Distance | $\sqrt{(X_0 - X_c)^2 + (Y_0 - Y_c)^2}$ | Euclidean distance is used in many machine learning algorithms as a default distance metric to measure the similarity between two recorded observations. It works on the principle of the Pythagoras theorem and signifies the shortest distance between two points. |
| (b) | Within-Cluster Sum of Square (WCSS) | $\sum_{p_i=1}^{p_m} distance(C_j, p_i)^2$ | WCSS is defined as the sum of the squared distance between each member of the cluster and its centroid. |