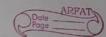
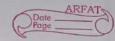


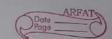
| Data Analytics | Regression modelling is widely |
|---|--|
| UNIT - 2 [One-Shot] | Regression modelling is widely used for prediction forecasting, and statistical strategies |
| Most important topics: | |
| Regression modeling and multivariate analysis. | * Types of regression models: |
| 2 Baysian networks | 1. Linear Regression: |
| 3 SVM and kernel methods. | Simple linear regression Models the relationship between two variables by fitting glinear equation to observed data. |
| 4. Time - series analysis. | variables by fitting a |
| 5 PCA and Juzzy decision trues | data. |
| 5. Stochastic search methods. | i.e. b/w an independent and a dependent variable. |
| @breitening | Multiple linear regression: Models the relationship between more than One independent and single dependent variable. |
| # Regression modeling: | than One independent and windle |
| · It is a statistical technique used | in blue one dependent and |
| to understand the relationship between a dependent variable and one or more independent variables. | i.e. b/w one dependent and multiple independent vaxiables |
| The goal is to the warmones. | Polynomial regression: Models the |
| The goal is to model the expected value of the dependent variable based on the values of the independent variables. | 2. Polynomial negression: Models the nelationship between the dependent variable and |
| of the independent variables | independent variable as an |



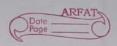


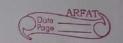
| 131 | nt deguee polynomial. | 5. | ogistic regression: Used for predicting binary outromes (yestro, true) false). |
|------|--|--------|---|
| | eg: predicting the growth of where growth accelerates at different reates. | | line, it fits S-shaped |
| 3. | | | probability of a particular |
| | Ridge regression: It includes a penalty term to avoid overfitting. This penalty term discourages large coefficients by adding the sum of their squares to cost function. i.e. for regularization. | | Jalu threshold |
| | their squares to cost function. | | e.g.: Predicting whether a customer |
| | eg: bredicting a students performance | | e.g: Predicting whether a customer will buy a product or not based on their age, behaviour, and browsing data. |
| 201 | e.g. bredicting a students penformance based on many related features like study has, activities, etc. | 6. | Random forest: It combines multiple |
| 4 | activities, etc. Lasso regression: It is also a regularization model that simplifies the complex models and eliminates some specific features for effective analysis. | | Random forest: It combines multiple decision trees to improve predictive performance and robustness of the model. It averages the predictions of all trees individually. |
| | models and eliminates some specific features for effective analysis. | | e.g. Bredicting a caris price |
| , K. | e.g. Bredicting weight on the basis of diet, excercise, lifestyle, etc. | Name A | mileage and brand. Obrevilearning |
| | | | |



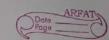


| | A. Lada |
|---|--|
| Multivariate analysis: | Bayrian networks: |
| It is a statistical approach used to understand the variables simultaneously. | models that represents the probabilistic relationships among a set of variables |
| It involves observing and analysing more than one outcome variable at a time. | They use Directed Acyclic Graphs (DAGs) where nodes and edges variables are used to represent grelationship blu model variables and their conditional probabilities. |
| product he buys but how factors like age | Key points: Nodes: Each node in a network |
| Techniques used types of MVA: | Edges: Dixected agricus b/w nodes that indicates conditional dependencies. |
| Clustering Factor analysis Multivariate regression | Probabilities: Each node has an associated probabilities that quantifies the likehood of different outromes. |
| MA helps in understanding relations reducing dimensions, and making informed lecisions in various fields. | Like, Share & Subscribe - @brevilearning YT |





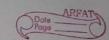
| example: | (#) | SVM | and | Kernel | methods: | 11/14 |
|---|------------|------------------|---|---|-----------------------------|--|
| Weather | * | SVM | (Support | Vector | Machines): | 9. |
| Genas wet | | These models and | used negres | supervised for | Jeogra danifica | ing Hien |
| · Weather (W): (an be sunny or rainy. · Sprinkler (S): (an be on or off. · Grass Wet (G): (an be wet or dry. | • | They (hyp | berplane) | the that classes | optimal best | boundary separates purplane support vectors |
| edges: $\begin{array}{c} \cdot \ \cup \ \longrightarrow \ S \\ \cdot \ \cup \ \longrightarrow \ Gr \\ \cdot \ S \ \longrightarrow \ Gr \end{array}$ | • | Key | points: | nates flat | poundary different | that classes. |
| Conditional probabilities: • P(W): Probability of weather (Rainy or Surry). | 1 | Support | Vectors: | Dota the defines | points hyperplane the | closest to that mangin. |
| P(S/W): Prob. of sprinkler being on or off. P(Gr/W, S): Prob. of grass wet or dry given the weather and sprinkler status. | lain. | Mangin | : The hyperplo supp SVM this sepanas | distance ne an wort v aims margin | d b/w the ectors for | the nearest |
| SUBSCRIBE - @brevileanning | | e.g: | : Classifying | emails | as s | nm or re |



-0 di

| | * Kernel Methods: | 3 RBF (Radial Basis Function) Kernel: |
|-------|---|---|
| | non-lineary data by transforming it into a high dimensional space without computing the co-ordinates explicitly. | Also known as brausian kennel its vensatile and great for non-linear data |
| | it into a high dimensional space without computing the | y Sigmoid kernel: Similar to the |
| | co-ordinates explicitly. | activation function in reunal networks, it's useful |
| Toles | It enables SVMs to handle. | for non-linear data but sometimes less effective than RBF kexnels. |
| | It enables SVMs to handle complex, non-linear data by using functions to map data into higher dimensions for better separation. | RBF kennels. Shrevileaning |
| | better separation. | |
| | Types of Konnels used in SVM: | ime - series analysis: It involves the collection analysis and interpretation of data points collected or recorded at specific time intervals to understand underlying patterns and predict future values * Companients of time - series: |
| 1 | Lineau Kernel: It is ideal for | points collected or recorded |
| | means of can be | understand underlying patterns and |
| | linearly separable data, means it can be best when data can be separated by a straight line. | predict juive values |
| 2. | D.A. | * Components of time - series: |
| | relationships in data. | · Triend: The long-term movement or direction: in the data over |
| | computationally more intensive | a period of time |
| | | e.g. Upward triend of stock-market our |
| | | |





| | Poge |
|--|---|
| Seasonality: Regular repeating patterns or cycles in data occurring at specific intervals. i.e. daily monthly, or annually. | PCA (Brincipal Component Analysis). It is a statistical technique used for dimentionality reduction. |
| e.g: Increased sales of ice-cream during summer. · Cyclical: long - term uppe - like patterns in the data not tied to a fixed calender | It transforms the original variables into a new set of unconversated variables called principal components, which capture the maximum variance in the data. |
| e.g. Busines cycles of economic expansion and contractions. | the data while retaining of much varience as possible |
| Noise: Random variations or inregularities in the data that do not follow any fathern. e.g.: Unexpected spikes in temperature readings due to servior | Step 1: Standardization: Ensures that the data is centered and scaled. |
| * Applications of Time Series Analysis: • Finance • Economics | Step 2: Covariance matrix: Computes the covariance matrix to understand how variables vary together. |
| · Weather forecast · Healthcare @browle arring. | Step 3: Eigen value and Eigenvectors: Compute all Eigenvalue and Eigenvectors of |

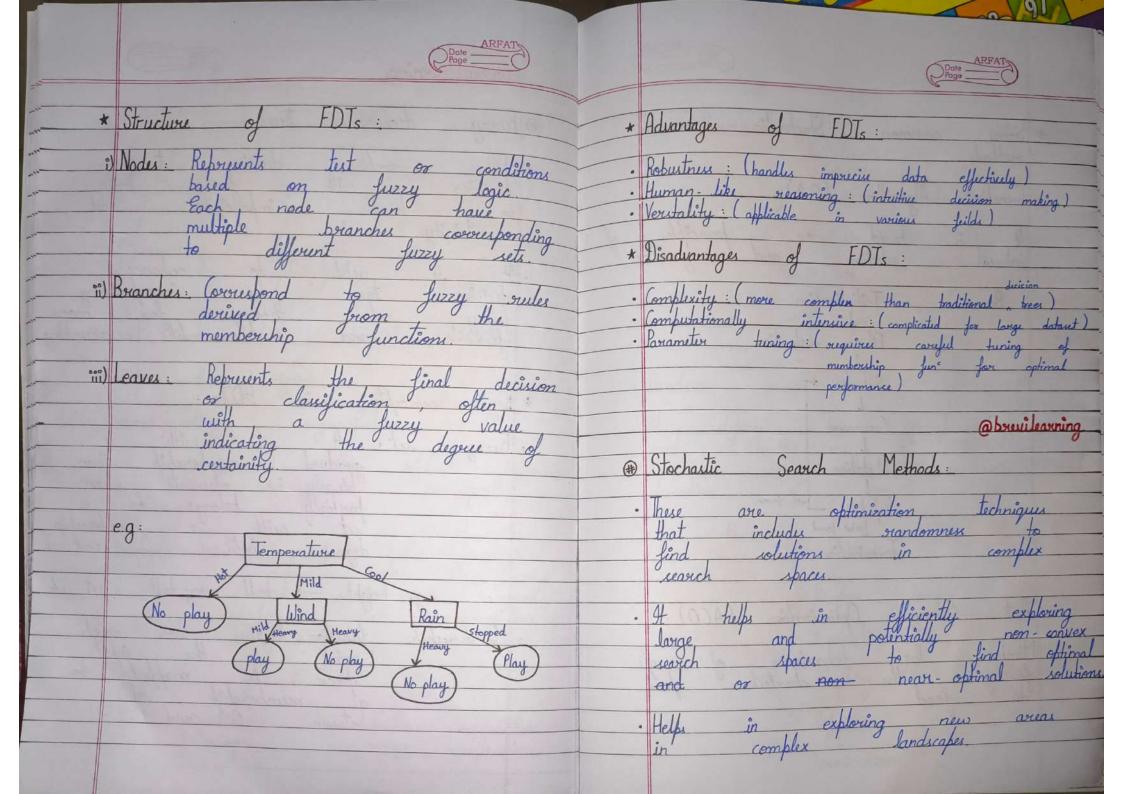
· Eigenvectors determines the direction of the principal components. Step 4: Sort and select Principal Components: · Sorts the eigenvalues in descending order and arrange the corresponding eigenvectors. Step 5: Transform

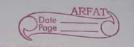
the covariance matrix.

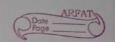
* Applications of PCA: · Data visualization · Feature extraction · Noise filtering · Image compression



| | Fuzzy decision trees: | |
|---|--|--|
| ı | | |
| + | TUIS combine decision | true |
| - | learning with fuzzy to handle impricition uncertainity in data | logic |
| | to handle impricision | and |
| 1 | FDTs combine decision learning with fuzzy to handle imprecision uncertainity in data | |
| | | |
| 1 | I wild to e | enhance |
| | decision by | incorporating |
| | Juzzy set theory | Joi more |
| | It is used to end decision trees by fuzzy set theory flexible and human-l | ike reasoning |
| | | The same of the sa |
| | Key concepts in FDTs: | |
| | | |
| | Fuzzu set: A set wi | the a |
| | manual members | chib than |
| | binary i.e. elemin | ts can |
| | partially belongs | to a |
| | set with a | membership |
| | Fuzzy set: A set wii graduol member binary i.e. elemin partially belongs set with a degree between | 0 and 1 |
| | U | 111 1 4 / |
| | e.g: height -> tall, very | tall, short, etc. |
| | M / I / I to Date | and. |
| | Membership function: Defines to point in the space is membership between 0 ar | inhut |
| | point in the | napped to |
| | space to the | Value |
| I | hatuun 0 ar | nd 1. |
| | Vestuali | |
| | | |







| * | Some common Stochastic Search | Process: Initialization |
|--------|---|--|
| 1. | Gienetic Algorithm (GiA): | Solution construction |
| | H is based on principles of natural selection and genetics. | Updation |
| | Process: Initialization | Repetition |
| | Fitness evaluation. | Termination |
| | Selection 4 | 3. Random search: |
| Phon 1 | Mulation (Marien) | It defines the search space and to the no of iterations that sets the boundaries and duration of search process. |
| | Repetition not found John Jourd Termination | Process: |
| 500 | Ant Colony Optimization (ACO): | Randem sampling Evaluation |
| | Timics the behaviour of anti- finding the shortest path | Tracking Best solution |
| | | Repetition |

