PUNE INSTITUTE OF COMPUTER TECHNOLOGY, PUNE

ACADEMIC YEAR: 2022-23

LAB MANUAL

DEPARTMENT: INFORMATION TECHNOLOGY

CLASS: T.E. **SEMESTER: V**

Subject Name: Lab Practice -1 (LP-1)

INDEX OF LAB EXPERIMENTS

Lab Expt. No.	Problem Statement
PART – A (Machine Learning)	
[- Implement any 6 assignments out of 7	

1.	Data preparation: Download heart dataset from following link. https://www.kaggle.com/zhaoyingzhu/heartcsv Perform following operation on given dataset. a) Find Shape of Data b) Find Missing Values c) Find data type of each column d) Finding out Zero's e) Find Mean age of patients f) Now extract only Age, Sex, ChestPain, RestBP, Chol. Randomly divide dataset in training (75%) and testing (25%). Through the diagnosis test I predicted 100 report as COVID positive, but only 45 of those were actually positive. Total 50 people in my sample were actually COVID positive. I have total 500 samples. Create confusion matrix based on above data and find I. Accuracy II. Precision III. Recall IV. F-1 score
2	Download temperature data from below link. https://www.kaggle.com/venky73/temperatures-of-india?select=temperatures.csv This data consists of temperatures of INDIA averaging the temperatures of all places monthwise. Temperatures values are recorded in CELSIUS A. Apply Linear Regression using suitable library function and predict the Month-wise temperature. B. Assess the performance of regression models using MSE, MAE and R-Square metrics C. Visualize simple regression model.

3	Every year many students give the GRE exam to get admission in foreign Universities. The dataset contains GRE Scores (out of 340), TOEFL Scores (out of 120), University Rating (out of 5), Statement of Purpose strength (out of 5), Letter of Recommendation strength (out of 5), Undergraduate GPA (out of 10), Research Experience (0=no, 1=yes), Admitted (0=no, 1=yes). Admitted is the target variable. Data Set Available on kaggle (The last column of the dataset needs to be changed to 0 or 1) Data Set: https://www.kaggle.com/mohansacharya/graduate-admissions. The counselor of the firm is supposed check whether the student will get an admission or not based on his/her GRE score and Academic Score. So, to help the counselor to take appropriate decisions build a machine learning model classifier using Decision tree to predict whether a student will get admission or not. A. Apply Data pre-processing (Label Encoding, Data Transformation....) techniques if necessary. B. Perform data-preparation (Train-Test Split) C. Apply Machine Learning Algorithm D. Evaluate Model.
4	A SMS unsolicited mail (every now and then known as cell smartphone junk mail) is any junk message brought to a cellular phone as textual content messaging via the Short Message Service (SMS). Use probabilistic approach (Naive Bayes Classifier / Bayesian Network) to implement SMS Spam Filtering system. SMS messages are categorized as SPAM or HAM using features like length of message, word depend, unique keywords etc. Download Data -Set from: http://archive.ics.uci.edu/ml/datasets/sms+spam+collection This dataset is composed by just one text file, where each line has the correct class followed by the raw message. A. Apply Data pre-processing (Label Encoding, Data Transformation....) techniques if B. necessary C. Perform data-preparation (Train-Test Split) D. Apply at least two Machine Learning Algorithms and Evaluate Models E. Apply Cross-Validation and Evaluate Models and compare performance. F. Apply Hyper parameter tuning and evaluate models and compare performance.

5	**Assignment on Clustering Techniques** Download the following customer dataset from below link: Data Set: https://www.kaggle.com/shwetabh123/mall-customers This dataset gives the data of Income and money spent by the customers visiting a shopping mall. The data set contains Customer ID, Gender, Age, Annual Income, Spending Score. Therefore, as a mall owner you need to find the group of people who are the profitable customers for the mall owner. Apply at least two clustering algorithms (based on Spending Score) to find the group of customers. A. Apply Data pre-processing (Label Encoding, Data Transformation....) techniques if necessary. B. Apply Machine Learning Algorithm C. Evaluate Model.
6	**Assignment on Association Rule Learning** Download Market Basket Optimization dataset from below link. Data Set: https://www.kaggle.com/hemanthkumar05/market-basket-optimization This dataset comprises the list of transactions of a retail company over the period of one week. It contains a total of 7501 transaction records where each record consists of the list of items sold in one transaction. Using this record of transactions and items in each transaction, find the association rules between items. There is no header in the dataset and the first row contains the first transaction, so mentioned header = None here while loading dataset. a. Follow following steps : b. Data Preprocessing c. Generate the list of transactions from the dataset d. Train Apriori algorithm on the dataset e. Visualize the list of rules Generated rules depend on the values of hyper parameters. By increasing the minimum confidence value and find the rules accordingly
7	Download the dataset of National Institute of Diabetes and Digestive and Kidney Diseases from below link:

	Data Set: https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians- diabetes.data.csv The dataset is has total 9 attributes where the last attribute is "Class attribute" having values 0 and 1. (1="Positive for Diabetes", 0="Negative") a. Load the dataset in the program. Define the ANN Model with Keras. Define at least two hidden layers. Specify the ReLU function as activation function for the hidden layer and Sigmoid for the output layer. b. Compile the model with necessary parameters. Set the number of epochs and batch size and fit the model. c. Evaluate the performance of the model for different values of epochs and batch sizes. d. Evaluate model performance using different activation functions Visualize the model using ANN Visualizer
PART – B (DAA / ADBMS)	
DAA	
1	Write a program to implement **Fractional knapsack using Greedy algorithm** and 0/1 knapsack using dynamic programming. Show that Greedy strategy does not necessarily yield an optimal solution over a **dynamic programming** approach.
2	Write a program to implement Bellman-Ford Algorithm using Dynamic Programming and verify the time complexity
3	Write a recursive program to find the solution of placing n queens on the chessboard so that no two queens attack each other using **Backtracking.**
4	Write a program to solve the travelling salesman problem and to print the path and the cost using **LC Branch and Bound.**
ADBMS	
1	Create a database with suitable example using **MongoDB** and implement A. Inserting and saving document (batch insert, insert validation) B. Removing document C. Updating document (document replacement, using modifiers, up inserts, updating multiple documents, returning updated documents) D. Execute at least 10 queries on any suitable MongoDB database that demonstrates following: a. Find and find One (specific values) b. Query criteria (Query conditionals, OR queries, $not, Conditional semantics) c. Type-specific queries (Null, Regular expression, Querying arrays) where queries d. Cursors (Limit, skip, sort, advanced query options)

2	Implement Map-reduce and aggregation, indexing with suitable example in. Demonstrate **MongoDB** the following: A. Aggregation framework B. Create and drop different types of indexes and explain () to show the advantage of the indexes.
3	**Case Study:** Design conceptual model using Star and Snowflake schema for any one database.

PART – C Mini-Project

Build the mini project based on the relevant applicable concepts of Machine Learning / DAA / ADBMS by forming teams of around 3 to 4 people.

Subject Coordinator **Head of Department**

Machine Learning

Assignment No -1

Title: Data preparation

Problem Statement:

Perform following operation on given dataset:

a) Find Shape of Data
b) Find Missing Values
c) Find data type of each column
d) Finding out Zero's
e) Find Mean age of patients
f) Now extract only Age, Sex, ChestPain, RestBP, Chol. Randomly divide dataset in training (75%) and testing (25%).
g) Through the diagnosis test I predicted 100 report as COVID positive, but only 45 of those were actually positive. Total 50 people in my sample were actually COVID positive. I have total 500 samples.

Create confusion matrix based on above data and find

i. Accuracy
ii. Precision
iii. Recall
iv. F-1 score

Objective: This assignment will help the students to realize what is need of data preparation

S/W Packages and H/W apparatus used:

Linux OS: Ubuntu/Windows , Jupyter notebook.
PC with the configuration as Pentium IV 1.7 GHz. 128M.B RAM, 40 G.B HDD, 15’’Color Monitor, Keyboard, Mouse

References:

1. Ethem Alpaydin, Introduction to Machine Learning, PHI 2nd Edition,2013.
2. Peter Flach: Machine Learning: The Art and Science of Algorithms that Make Sense of Data,Cambridge University Press, Edition 2012.

Theory:

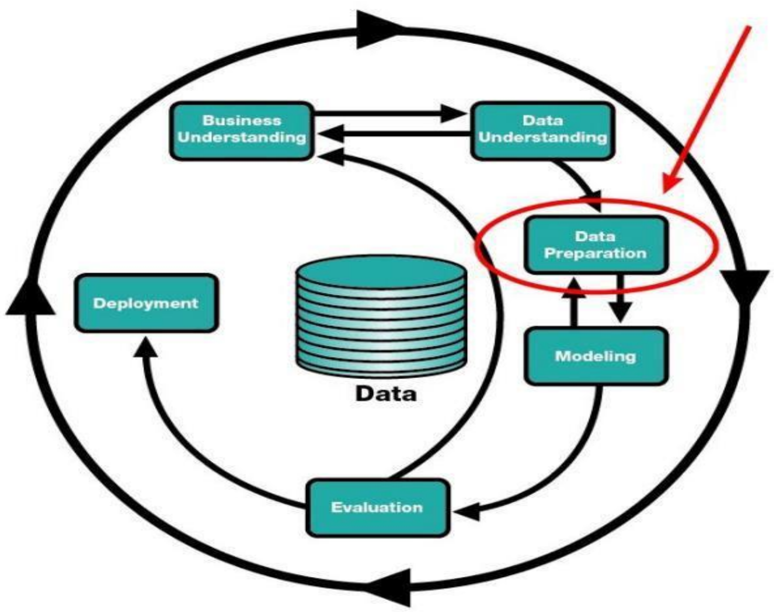
Data Preparation

Data preparation (also referred to as “data preprocessing”) is the process of transforming raw data so that data scientists and analysts can run it through machine learning algorithms to uncover insights or make predictions.

Why is Data Preparation Important?

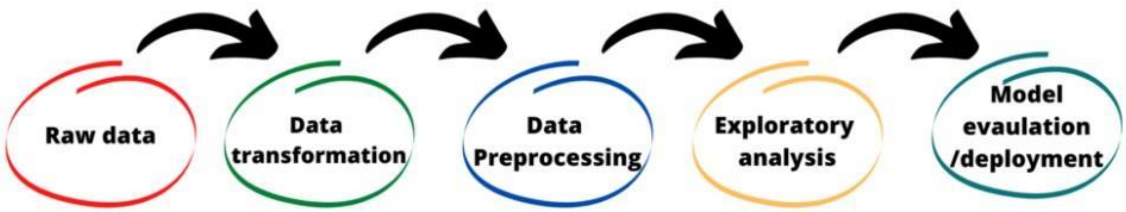
Most machine learning algorithms require data to be formatted in a very specific way, so datasets generally require some amount of preparation before they can yield useful insights. Some datasets have values that are missing, invalid, or otherwise difficult for an algorithm to process. If data is missing, the algorithm can't use it. If data is invalid, the algorithm produces less accurate or even misleading outcomes. Some datasets are relatively clean but need to be shaped (e.g., aggregated or pivoted) and many datasets are just lacking useful business context (e.g., poorly defined ID values), hence the need for feature enrichment. Good data preparation produces clean and well-curated data which leads to more practical, accurate model outcomes.

It is the most required process before feeding the data into the machine learning model. The reason behind that the data set needs to be different and specific according to the model so that we have to find out the required features of that data. The data preparation process offers a method via which we can prepare the data for defining the project and also for the project evaluation of ML algorithms. Different many predicting machine learning models are there with a different process but some of the processes are common that are performed in every model, and also it allows us to find out the actual business problem and their solutions. Some of the data preparation processes are:



1. **Determine the problems**
2. **Data cleaning**
3. **Feature selection**

4. **Data transformation**
5. **feature engineering**
6. **Dimensionality reduction**



1. **Determine the problems:**

This step tells us about the learning method of the project to find out the results for future prediction or forecasting. For example, which ML model suitable for the data set regression or classification or clustering algorithms. This includes data collection that is useful for predicting the result and also involving the communication to project stakeholders and domain expertise. We use classification and regression models for categorical and numerical data respectively.

It includes determining the relevant attributes with the stied data in form of .csv, .html, .json, .doc, and many, also for unstructured data in a form for audio, video, text, images, etc for scanning and detect the patterns of data with searching and identifying the data that have taken from external repositories.

2. **Data cleaning:**

After collecting the data, it is very necessary to clean that data and make it proper for the ML model. It includes solving problems like outliers, inconsistency, missing values, incorrect, skewed, and trends. Cleaning the data is very important as the model learning from that data only, so if we feed inconsistent, appropriate data to model it will return garbage only, so it is required to make sure that the data does not contains any unseen problem. For example, if we have a data set of sales, it might be possible that it contains some features like height, age, that cannot help in the model building so we can remove it. We generally remove the null values columns, fill the missing values, make the data set consistent, and remove the outliers and skewed data in data cleaning.

3. **Feature selection:**

Sometimes we face the problem of identifying the related features from the set of data and deleting the irrelevant and less important data without touching the target variables to get the better accuracy of the model. Features selection plays a wide role in building a machine learning model that impacts the performance and accuracy of the model. It is that process which contributes mostly to the predictions or output that we need by selecting the features automatically or manually. If we have irrelevant data that would cause the model with overfitting and underfitting.

The benefits of feature selection:

1. Reduce the overfitting/underfitting
2. Improves the accuracy
3. Reduced training/testing time
4. Improves performance

4. Data transformation:

Data transformation is the process that converts the data from one form to another. It is required for data integration and data management. In data transformation, we can change the types of data, clear the data removing the null values or duplicate values, and get enrich data that depends on the requirements of the model. It allows us to perform data mapping that determines how individual features are mapped, modified, filtered, aggregated, and joined. Data transformation is needed for both structured and unstructured data but it is time consuming, costly, slow.

5. Feature engineering:

Every ML algorithms use some input data for giving required output and this input required some features which are in a structured form. To get the proper result the algorithms required features with some specific characteristics which we find out with feature engineering. we need to perform different feature engineering on different datasets and we can observe their effect on model performance. Here I am listing out the techniques of feature engineering.

1. Imputation
2. Handling outliers
3. Binning

4. Log transform
5. one-hot encoding
6. Grouping operations
7. Feature split
8. Scaling

6. Dimensionality reduction:

When we use the dataset for building an ML model, we need to work with 1000s of features that cause the curse of dimensionality, or we can say that it refers to the process to convert a set of data. For the ML model, we have to access a large amount of data and that large amount of data can lead us in a situation where we can take possible data that can be available to feed it into a forecasting model to predict and give the result of the target variable. It reduced the time that is required for training and testing our machine learning model and also helps to eliminate over-fitting. It is kind of zipping the data for the model.

Implementation:

```
import numpy as nm
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
df = pd.read_csv("Heart.csv")
```

```
df.head(8)
```

	Unnamed: 0	Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak	Slope	Ca	Thal	AHD
0	1	63	1	typical	145	233	1	2	150	0	2.3	3	0.0	fixed	No
1	2	67	1	asymptomatic	160	286	0	2	108	1	1.5	2	3.0	normal	Yes

2	3	67	1	asymptomatic	120	229	0	2	129	1	2.6	2	2.0	reversable	Yes
3	4	37	1	nonanginal	130	250	0	0	187	0	3.5	3	0.0	normal	No
4	5	41	0	nontypical	130	204	0	2	172	0	1.4	1	0.0	normal	No
5	6	56	1	nontypical	120	236	0	0	178	0	0.8	1	0.0	normal	No
6	7	62	0	asymptomatic	140	268	0	2	160	0	3.6	3	2.0	normal	Yes
7	8	57	0	asymptomatic	120	354	0	0	163	1	0.6	1	0.0	normal	No

In [ ]:

```
df.shape
```

```
(303, 15)
df.isnull().sum()
```

Out[ ]:

```
Unnamed: 0    0
Age           0
Sex           0
ChestPain     0
RestBP        0
Chol          0
Fbs           0
RestECG       0
MaxHR         0
ExAng         0
Oldpeak       0
Slope         0
Ca            4
Thal          2
```

```
AHD             0
dtype: int64
```

In [ ]:

```
print("Total missing values: ", df.isnull().sum().sum())
```

```
Total missing values:  6
```

In [ ]:

```
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 15 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  303 non-null    int64
 1   Age         303 non-null    int64
 2   Sex         303 non-null    int64
 3   ChestPain   303 non-null    object
 4   RestBP      303 non-null    int64
 5   Chol        303 non-null    int64
 6   Fbs         303 non-null    int64
 7   RestECG     303 non-null    int64
 8   MaxHR       303 non-null    int64
 9   ExAng       303 non-null    int64
 10  Oldpeak     303 non-null    float64
 11  Slope       303 non-null    int64
 12  Ca          299 non-null    float64
 13  Thal        301 non-null    object
 14  AHD         303 non-null    object
dtypes: float64(2), int64(10), object(3)
memory usage: 32.0+ KB
```

In [ ]:

```
df.dtypes
```

Out[ ]:

```
Unnamed: 0      int64
Age             int64
```

```
Sex               int64
ChestPain        object
RestBP            int64
Chol              int64
Fbs               int64
RestECG           int64
MaxHR             int64
ExAng             int64
Oldpeak         float64
Slope             int64
Ca              float64
Thal             object
AHD              object
dtype: object
```

In [ ]:

```
(df == 0).sum(axis=0)
```

Out[ ]:

```
Unnamed: 0      0
Age             0
Sex            97
ChestPain       0
RestBP          0
Chol            0
Fbs           258
RestECG       151
MaxHR           0
ExAng         204
Oldpeak        99
Slope           0
Ca            176
Thal            0
AHD             0
dtype: int64
```

In [ ]:

```
mean_age =df['Age'].mean()

mean_age
```

Out[ ]:

```
54.43894389438944
```

In [ ]:

```
df.columns
```

Out[ ]:

```
Index(['Unnamed: 0', 'Age', 'Sex', 'ChestPain', 'RestBP', 'Chol',
'Fbs',

       'RestECG', 'MaxHR', 'ExAng', 'Oldpeak', 'Slope', 'Ca', 'Thal',
'AHD'],

      dtype='object')
```

In [ ]:

```
df2 = df.filter(['Age','Sex','ChestPain','RestBP','Chol'])
```

In [ ]:

```
df2
```

Out[ ]:

	Age	Sex	ChestPain	RestBP	Chol
0	63	1	typical	145	233
1	67	1	asymptomatic	160	286
2	67	1	asymptomatic	120	229
3	37	1	nonanginal	130	250
4	41	0	nontypical	130	204
...	...	...	...	...	...
298	45	1	typical	110	264
299	68	1	asymptomatic	144	193
300	57	1	asymptomatic	130	131

301	57	0	nontypical	130	236
302	38	1	nonanginal	138	175

303 rows × 5 columns

```
mean = df['Ca'].mean()
df['Ca'].fillna(value=mean,inplace=True)
```

```
mode = df['Thal'].mode().iloc[0]
df['Thal'].fillna(value=mode, inplace=True)
```

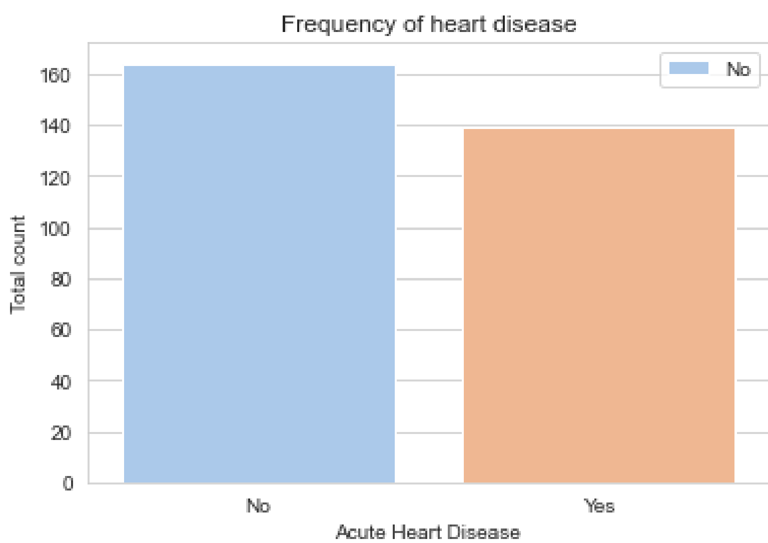
```
df.isnull().sum()
```

```
Unnamed: 0    0
Age           0
Sex           0
ChestPain     0
RestBP        0
Chol          0
Fbs           0
RestECG       0
MaxHR         0
ExAng         0
Oldpeak       0
Slope         0
Ca            0
Thal          0
AHD           0
dtype: int64
```

```
sns.countplot(x='AHD',data=df, palette='pastel')
sns.set_style("whitegrid")
```

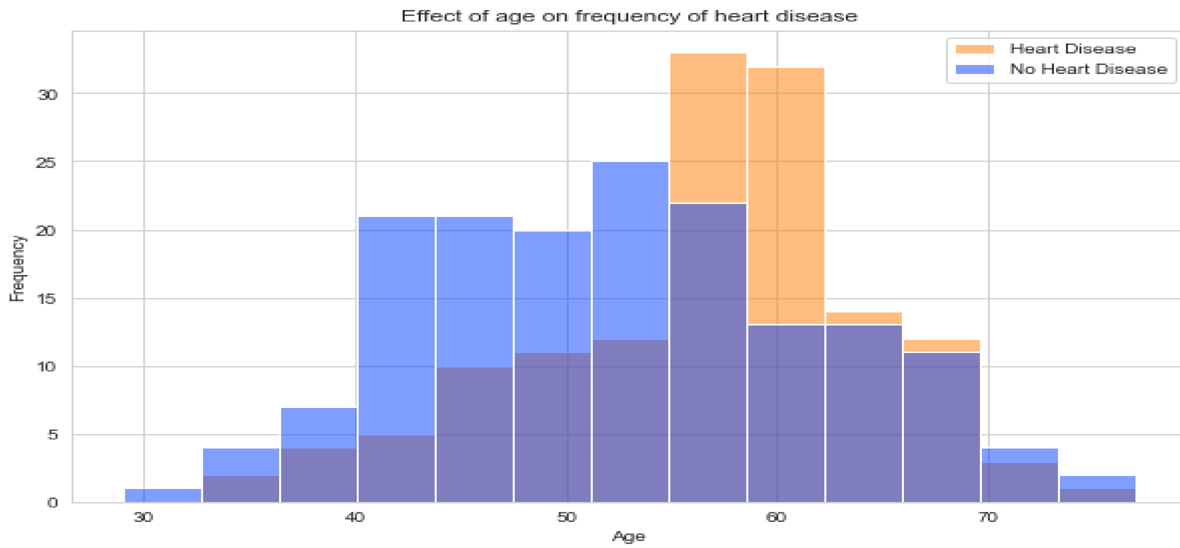
```
plt.xlabel("Acute Heart Disease")
plt.ylabel("Total count")
plt.title("Frequency of heart disease")
plt.legend(['No','Yes'],loc='upper right')
```

```
<matplotlib.legend.Legend at 0x6d758f8>
```



In [ ]:

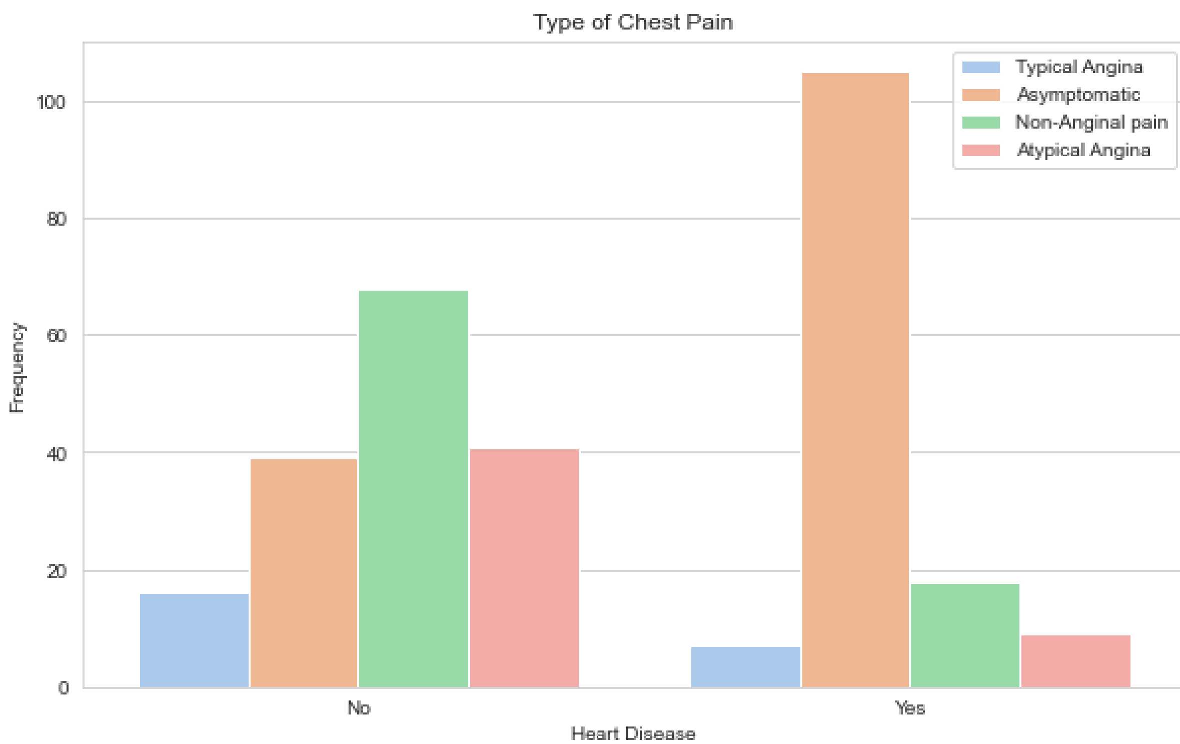
```
fig, ax = plt.subplots()
fig.set_size_inches(10, 6)
sns.histplot(x="Age", data=df, hue="AHD", palette="bright")
sns.set_style("whitegrid")
plt.title("Effect of age on frequency of heart disease")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.legend(["Heart Disease","No Heart Disease"])
plt.show()
```



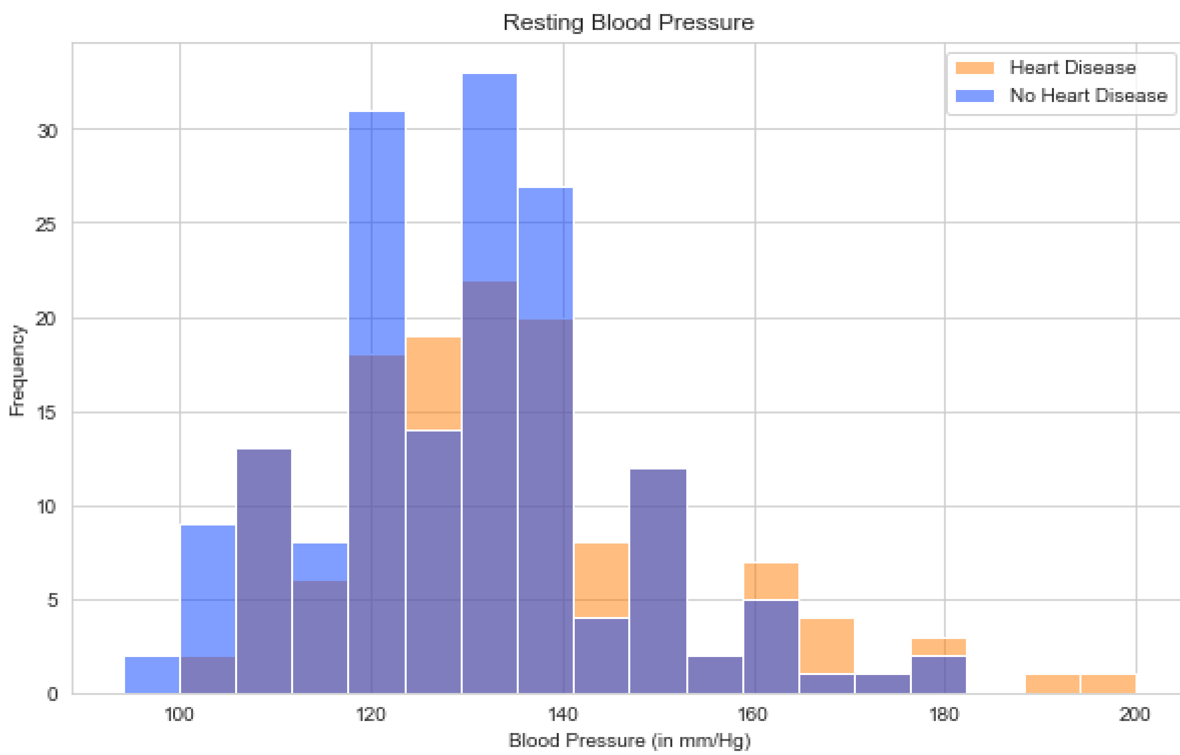

```
df['ChestPain'].unique()
```

```
array(['typical', 'asymptomatic', 'nonanginal', 'nontypical'],
      dtype=object)
```

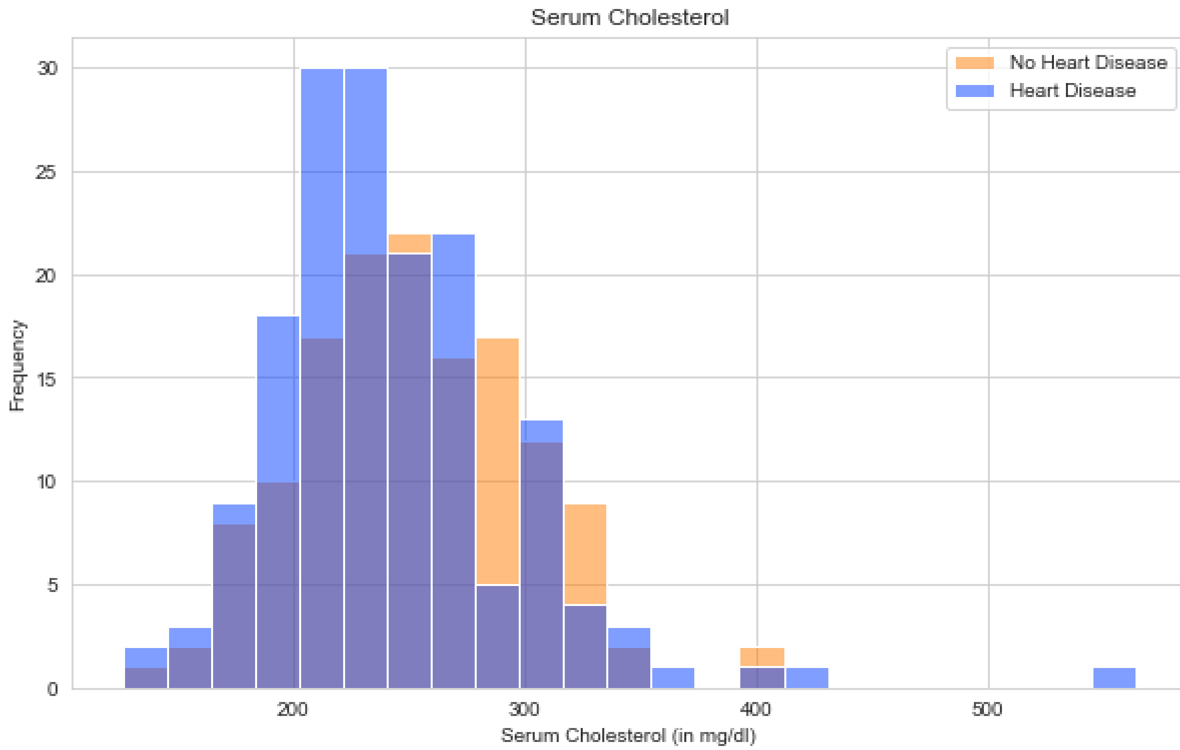
```
fig, ax = plt.subplots()
fig.set_size_inches(10, 6)
sns.countplot(x="AHD", hue="ChestPain", data=df, palette="pastel")
plt.title("Type of Chest Pain")
plt.xlabel("Heart Disease")
plt.ylabel("Frequency")
plt.legend(["Typical Angina","Asymptomatic", "Non-Anginal pain",
"Atypical Angina"])
plt.show()
```



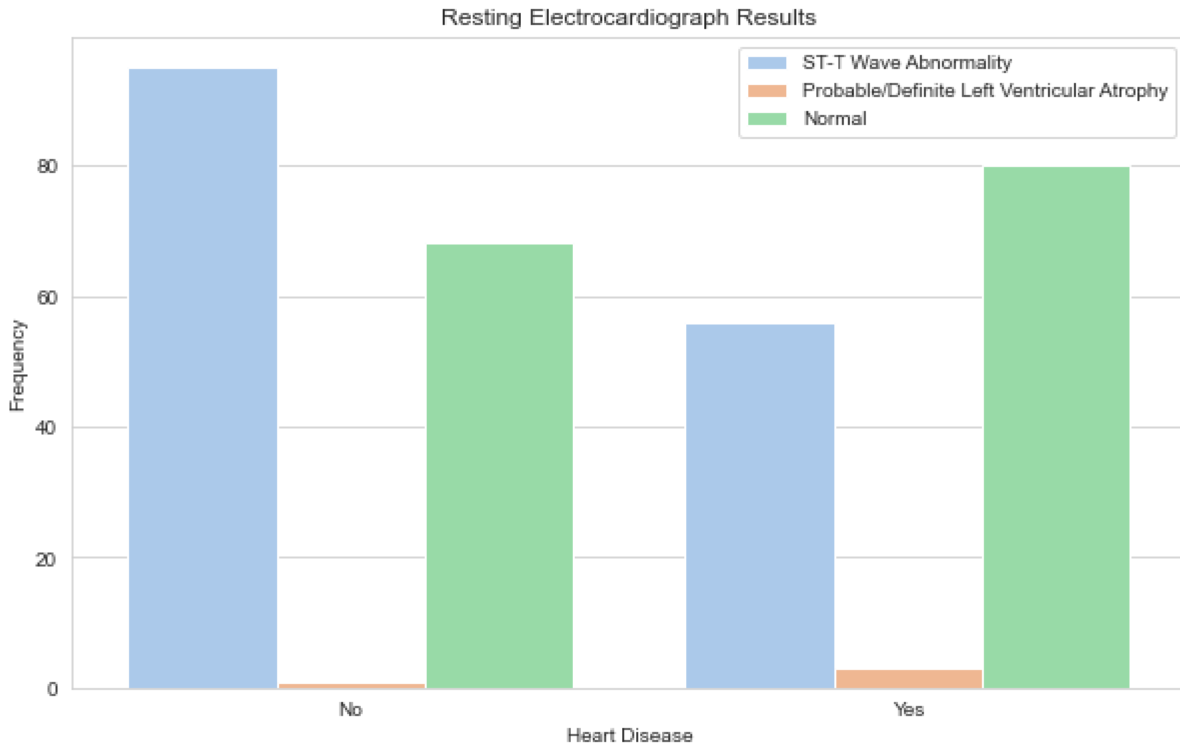

```
fig, ax = plt.subplots()
fig.set_size_inches(10, 6)
sns.histplot(x="RestBP" , data=df, hue="AHD", palette="bright")
sns.set_style("whitegrid")
plt.title("Resting Blood Pressure")
plt.xlabel("Blood Pressure (in mm/Hg)")
plt.ylabel("Frequency")
plt.legend(["Heart Disease","No Heart Disease"])
plt.show()
```




```
fig, ax = plt.subplots()
fig.set_size_inches(10, 6)
sns.histplot(x="Chol" , data=df, hue="AHD", palette="bright")
sns.set_style("whitegrid")
plt.title("Serum Cholesterol")
plt.xlabel("Serum Cholesterol (in mg/dl)")
plt.ylabel("Frequency")
plt.legend(["No Heart Disease","Heart Disease"])
plt.show()
```




```
fig, ax = plt.subplots()
fig.set_size_inches(10, 6)
sns.countplot(x="AHD", hue="RestECG", data=df, palette="pastel")
plt.title("Resting Electrocardiograph Results")
plt.xlabel("Heart Disease")
plt.ylabel("Frequency")
plt.legend(["ST-T Wave Abnormality", "Probable/Definite Left
Ventricular Atrophy", "Normal"])
plt.show()
```




```
X = df[['Age','Sex','ChestPain','RestBP','Chol','RestECG','MaxHR']]
Y= df['AHD']
```

```
#X= df.values
#Y= df.AHD.values
```

```
from sklearn.model_selection import train_test_split


X_train, Y_train, X_test, Y_test =
train_test_split(X,Y,test_size=0.25)
```

```
X_train.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 227 entries, 245 to 231
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Age         227 non-null    int64
 1   Sex         227 non-null    int64
```

```
 2   ChestPain  227 non-null    object
 3   RestBP     227 non-null    int64
 4   Chol       227 non-null    int64
 5   RestECG    227 non-null    int64
```

```
 6   MaxHR      227 non-null    int64
dtypes: int64(6), object(1)
memory usage: 13.3+ KB
```

```
Y_train.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 76 entries, 121 to 53
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Age        76 non-null     int64
 1   Sex        76 non-null     int64
 2   ChestPain  76 non-null     object
 3   RestBP     76 non-null     int64
 4   Chol       76 non-null     int64
 5   RestECG    76 non-null     int64
 6   MaxHR      76 non-null     int64
dtypes: int64(6), object(1)
memory usage: 4.5+ KB
```

Conclusion:

Data preparation is recognized for helping businesses and analytics to get ready and prepare the data for operations.

References:

[1]https://medium.com/@learnbay/6-most-important-steps-for-data-preparation-in-machine-learning-61ae88ab8628

Assignment No -2

Title: Regression technique

Problem Statement:

This data consists of temperatures of INDIA averaging the temperatures of all place's month wise. Temperatures values are recorded in CELSIUS

a) Apply Linear Regression using suitable library function and predict the Month-wise temperature.
b) Assess the performance of regression models using MSE, MAE and R-Square metrics
c) Visualize simple regression model.

Objective: This assignment will help the students to realize how the Linear Regression can be used and predictions using the same can be performed.

S/W Packages and H/W apparatus used:

Linux OS: Ubuntu/Windows, Jupyter notebook.
PC with the configuration as Pentium IV 1.7 GHz. 128M.B RAM, 40 G.B HDD, 15''Color Monitor, Keyboard, Mouse

References:

1. Ethem Alpaydin, Introduction to Machine Learning, PHI 2nd Edition,2013.
2. Peter Flach: Machine Learning: The Art and Science of Algorithms that Make Sense of Data, Cambridge University Press, Edition 2012.

Theory:

Definition of Linear Regression

In layman terms, we can define linear regression as **it is used for learning the linear relationship between the target and one or more forecasters**, and it is probably one of the most popular and well inferential algorithms in statistics. Linear regression endeavours to demonstrate the connection between two variables by fitting a linear equation to observed information. One variable is viewed as an explanatory variable, and the other is viewed as a dependent variable.

Types of Linear Regression

Normally, linear regression is divided into two types: Multiple linear regression and Simple linear regression.

1. **Multiple Linear Regression**

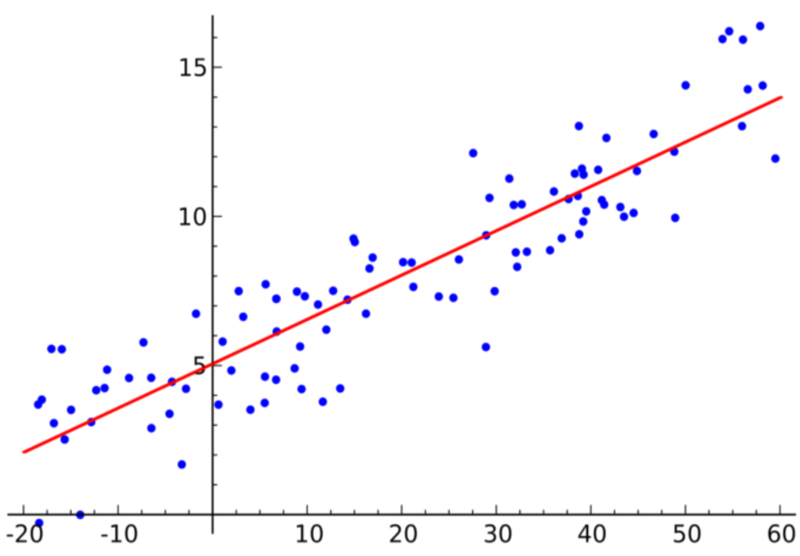
In this type of linear regression, we always attempt to discover the relationship between two or more independent variables or inputs and the corresponding dependent variable or output and the independent variables can be either continuous or categorical.

This linear regression analysis is very helpful in several ways like it helps in foreseeing trends, future values, and moreover predict the impacts of changes.

2. **Simple Linear Regression**

In simple linear regression, we aim to reveal the relationship between a single independent variable or you can say input, and a corresponding dependent variable or output. We can discuss this in a simple line as $y = \beta 0 + \beta 1x + \varepsilon$

Here, Y speaks to the output or dependent variable, β0 and β1 are two obscure constants that speak to the intercept and coefficient that is slope separately, and the error term is ε Epsilon.We can also discuss this in the form of a graph and here is a sample simple linear regression model graph.



Simple Linear Regression graph

What Actually is Simple Linear Regression?

It can be described as a method of statistical analysis that can be used to study the relationship between two quantitative variables.

Primarily, there are two things which can be found out by using the method of simple linear regression:

1. **Strength of the relationship between the given duo of variables.** (For example, the relationship between global warming and the melting of glaciers)
2. **How much the value of the dependent variable is at a given value of the independent variable.** (For example, the amount of melting of a glacier at a certain level of global warming or temperature)

Regression models are used for the elaborated explanation of the relationship between two given variables. There are certain types of regression models like logistic regression models, nonlinear regression models, and linear regression models. The linear regression model fits a straight line into the summarized data to establish the relationship between two variables.

Assumptions of Linear Regression

To conduct a simple linear regression, one has to make certain assumptions about the data. This is because it is a parametric test. The assumptions used while performing a simple linear regression are as follows:

- **Homogeneity of variance (homoscedasticity)-** One of the main predictions in a simple linear regression method is that the size of the error stays constant. This simply means that in the value of the independent variable, the error size never changes significantly.
- **Independence of observations-** All the relationships between the observations are transparent, which means that nothing is hidden, and only valid sampling methods are used during the collection of data.
- **Normality-** There is a normal rate of flow in the data.

These three are the assumptions of regression methods.

However, there is one additional assumption that has to be taken into consideration while specifically conducting a linear regression.

- **The line is always a straight line-** There is no curve or grouping factor during the conduction of a linear regression. There is a linear relationship between the variables (dependent variable and independent variable). If the data fails the assumptions of homoscedasticity or normality, a nonparametric test might be used. (For example, the Spearman rank test)

Example of data that fails to meet the assumptions: One may think that cured meat consumption and the incidence of colorectal cancer in the U.S have a linear relationship. But later on, it comes to the knowledge that there is a very high range difference between the collection of data of both the variables. Since the homoscedasticity assumption is being violated here, there can be no linear regression test. However, a Spearman rank test can be performed to know about the relationship between the given variables.

Applications of Simple Linear Regression

1. **Marks scored by students based on number of hours studied (ideally)-** Here marks scored in exams are dependent and the number of hours studied is independent.
2. **Predicting crop yields based on the amount of rainfall-** Yield is a dependent variable while the measure of precipitation is an independent variable.
3. **Predicting the Salary of a person based on years of experience-** Therefore, Experience becomes the independent while Salary turns into the dependent variable.

Limitations of Simple Linear Regression

Indeed, even the best information doesn't recount a total story. Regression investigation is ordinarily utilized in examination to set up that a relationship exists between variables. However, correlation isn't equivalent to causation: a connection between two variables doesn't mean one causes the other to occur. Indeed, even a line in a simple linear regression that fits the information focuses well may not ensure a circumstances and logical results relationship.

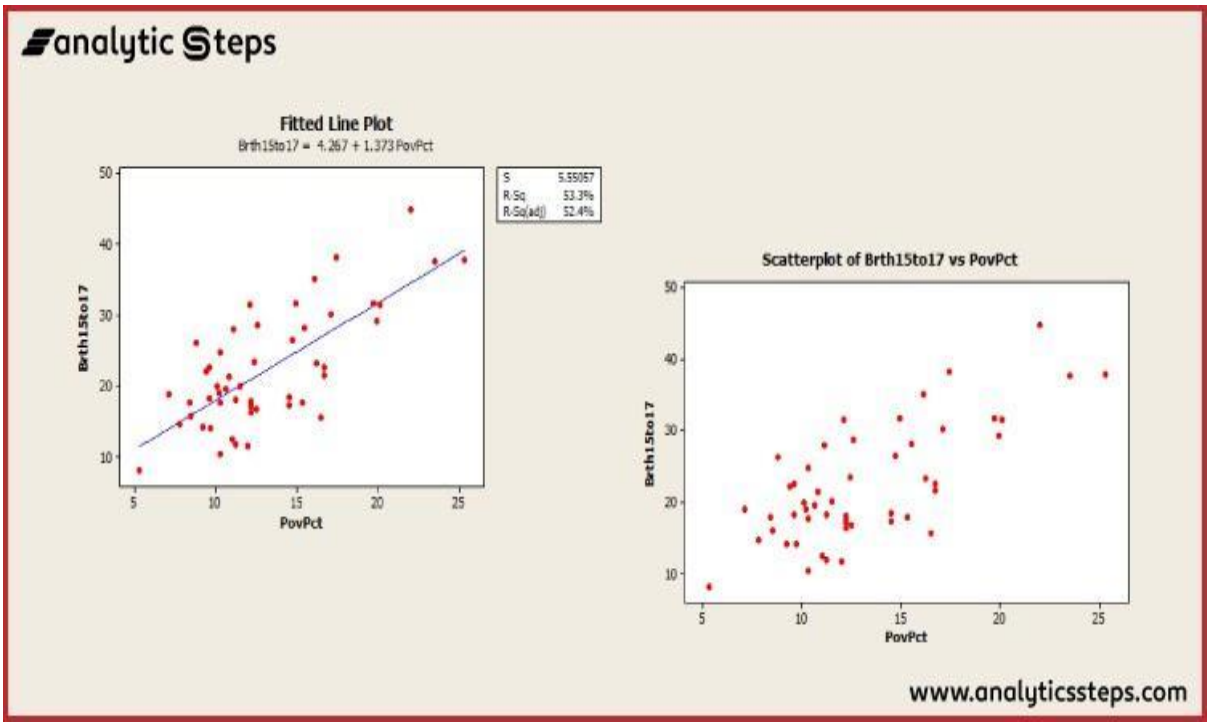
Utilizing a linear regression model will permit you to find whether a connection between variables exists by any means. To see precisely what that relationship is and whether one variable cause another, you will require extra examination and statistical analysis.

Examples of Simple Linear Regression

Now, let’s move towards understanding simple linear regression with the help of an example. We will take an example of teen birth rate and poverty level data.

This dataset of size n = 51 is for the 50 states and the District of Columbia in the United States. The variables are y = year 2002 birth rate for each 1000 females 15 to 17 years of age and x = destitution rate, which is the percent of the state's populace living in families with wages underneath the governmentally characterized neediness level. (Information source: Mind On Statistics, 3rd version, Utts and Heckard).

Below is the graph (right image) in which you can see the (birth rate on the vertical) is indicating a normally linear relationship, on average, with a positive slope. As the poverty level builds, the birth rate for 15 to 17-year-old females will in general increment too.



Example graph of simple linear regression

Here is another graph (left graph) which is showing a regression line superimposed on the data.

The condition of the fitted regression line is given close to the highest point of the plot. The condition should express that it is for the "average" birth rate (or "anticipated" birth rate would be alright as well) as a regression condition portrays the normal estimation of y as a component of at least one x-variables. In statistical documentation, the condition could be composed y^=4.267+1.373x.

- The interpretation of the slope (value = 1.373) is that the 15 to 17-year-old birth rate increases 1.373 units, on average, for each one unit (one per cent) increase in the poverty rate.

- The translation of the intercept (value=4.267) is that if there were states with a population rate = 0, the anticipated normal for the 15 to 17-year-old birth rate would be 4.267 for those states. Since there are no states with a poverty rate = 0 this understanding of the catch isn't basically significant for this model.
- In the chart with a repression line present, we additionally observe the data that s = 5.55057 and r2 = 53.3%.
- The estimation of s discloses to us generally the standard deviation of the contrasts between the y-estimations of individual perceptions and expectations of y dependent on the regression line. The estimation of r2 can be deciphered to imply that destitution rates "clarify" 53.3% of the noticed variety in the 15 to 17-year-old normal birth paces of the states.

The R2 (adj) value (52.4%) is a change in accordance with R2 dependent on the number of x-variables in the model (just one here) and the example size. With just a single x-variable, the charged R2 isn't significant.

Implementation:

```
#Import Libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

Importing the csv file

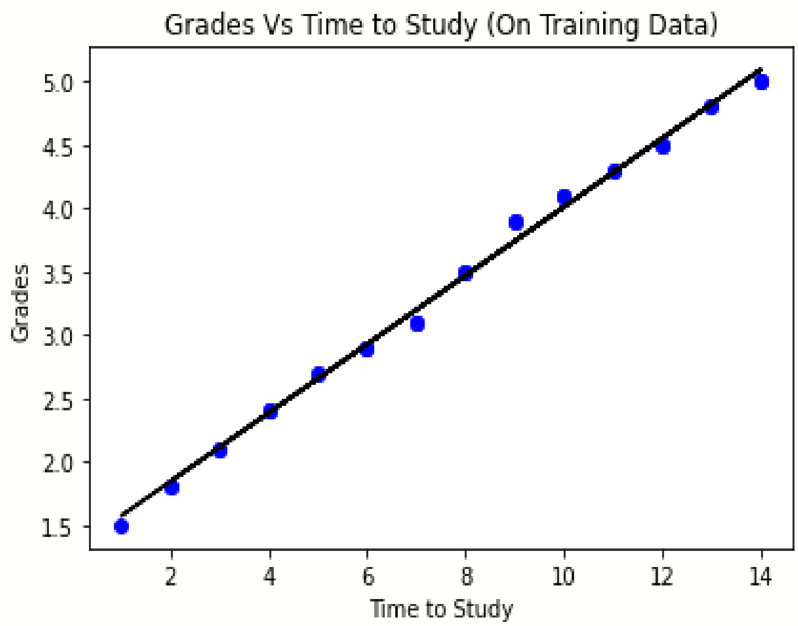
```
from google.colab import files
uploaded = files.upload()

#Read Student Grades .csv file and divide the data into dependent and inde
pendent variables.
data = pd.read_csv('Student_Grades_Data.csv')
data.head()

data.shape

(50, 2)

X = data.iloc[:, :-1].values
y = data.iloc[:, 1].values

X
array([[ 1],
       [ 5],
       [ 7],
       [ 3],
```

```
       [ 2],
       [ 9],
       [ 6],
       [12],
       [11],
       [ 2],
       [ 4],
       [ 8],
       [13],
       [ 9],
       [14],
       [10],
       [ 6],
       [12],
       [ 1],
       [ 4],
       [14],
       [10],
       [11],
       [ 4],
       [ 5],
       [ 8],
       [ 1],
       [ 2],
       [ 3],
       [ 7],
       [ 8],
       [14],
       [ 7],
       [ 8],
       [ 1],
       [ 2],
       [ 3],
       [ 4],
       [ 5],
       [ 6],
       [ 7],
       [ 8],
       [ 9],
       [10],
       [11],
       [12],
       [13],
       [14],
       [ 8],
       [ 2]])
```

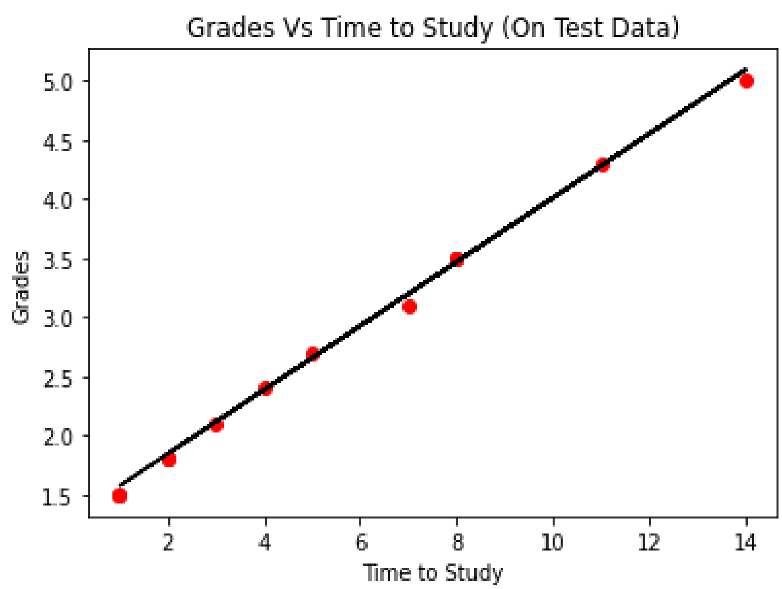
```
Y
```

```
array([1.5, 2.7, 3.1, 2.1, 1.8, 3.9, 2.9, 4.5, 4.3, 1.8, 2.4, 3.5, 4.8,
       3.9, 5. , 4.1, 2.9, 4.5, 1.5, 2.4, 5. , 4.1, 4.3, 2.4, 2.7, 3.5,
       1.5, 1.8, 2.1, 3.1, 3.5, 5. , 3.1, 3.5, 1.5, 1.8, 2.1, 2.4, 2.7,
```

```
       2.9, 3.1, 3.5, 3.9, 4.1, 4.3, 4.5, 4.8, 5. , 3.5, 1.8])

#Split the data into training and test datasets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,
 random_state = 0)

y_test

array([2.1, 3.5, 2.4, 3.5, 3.1, 1.8, 2.7, 5. , 4.3, 1.8, 3.5, 1.8, 1.5,
       1.5, 1.5])

#Fit the Simple Linear Regression Model
from sklearn.linear_model import LinearRegression
LinReg = LinearRegression()
LinReg.fit(X_train, y_train)

#Print the
print(f'a0 = {LinReg.intercept_}')
print(f'a1 = {LinReg.coef_}')

#Predicted grade scores from test dataset
y_predict = LinReg.predict(X_test)
y_predict

#Actual grade scores from test dataset
y_test

#Grades Vs Time to Study visualization on Training Data
plt.scatter(X_train, y_train, color='Blue')
plt.plot(X_train, LinReg.predict(X_train), color='Black')
plt.title('Grades Vs Time to Study (On Training Data)')
plt.xlabel('Time to Study')
plt.ylabel('Grades')
plt.show()
```




```
#Grades Vs Time to Study visualization on Test Data
plt.scatter(X_test, y_test, color='Red')
plt.plot(X_train, LinReg.predict(X_train), color='Black')
plt.title('Grades Vs Time to Study (On Test Data)')
plt.xlabel('Time to Study')
plt.ylabel('Grades')
plt.show()
```




```
#Predicting Grade of a student when he studied for 10 Hrs. Example of how
to pass an external value,
#Independent of Test or Training Dataset

Predict_Grade = LinReg.predict([[10]])
Predict_Grade
```

```
#Model Evaluation using R-Square
from sklearn import metrics
r_square = metrics.r2_score(y_test, y_predict)
print('R-Square Error:', r_square)

#Model Evaluation using Mean Square Error (MSE)
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_predict)
)

#Model Evaluation using Root Mean Square Error (RMSE)
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_tes
t, y_predict)))

#Model Evaluation using Mean Absolute Error (MAE)
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_predic
t))
```

Conclusion

Simple linear regression is a regression model that figures out the relationship between one independent variable and one dependent variable using a straight line.

References:

[1]RiyaKumari,https://www.analyticssteps.com/blogs/simple-linear-regression-applications-limitations-examples

Assignment No -3

Title: Classification using Machine Learning

Problem Statement:

Perform following operations on given dataset:

a) Apply Data pre-processing (Label Encoding, Data Transformation....) techniques if necessary.
b) Perform data-preparation (Train-Test Split)
c) Apply Decision tree classification Algorithm
d) Evaluate Model.

Objective:

This assignment will help the students to realize how the decision tree classifier can be used and predictions using the same can be performed.

S/W Packages and H/W apparatus used:

Linux OS: Ubuntu/Windows , Jupyter notebook.
PC with the configuration as Pentium IV 1.7 GHz. 128M.B RAM, 40 G.B HDD,
15''Color Monitor, Keyboard, Mouse

References:

1. *Ethem Alpaydin, Introduction to Machine Learning, PHI 2nd Edition,2013.*
2. *Peter Flach: Machine Learning: The Art and Science of Algorithms that Make Sense of Data,Cambridge University Press, Edition 2012..*

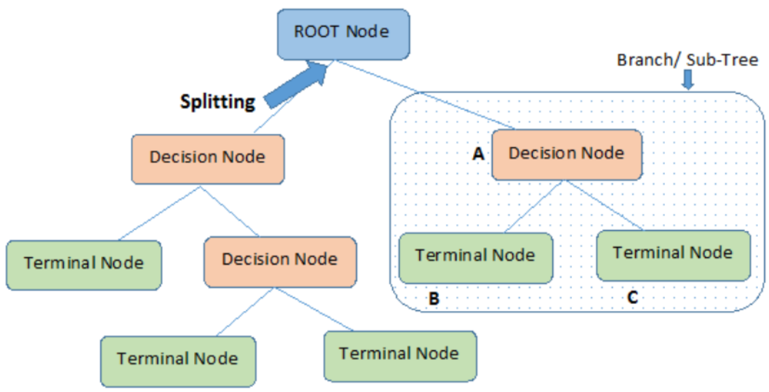
Theory:

Classification:

Classification is **a process of categorizing a given set of data into classes**, It can be performed on both structured or unstructured data. The process starts with predicting the class of given data points. The classes are often referred to as target, label or categories.

What is a Decision Tree?

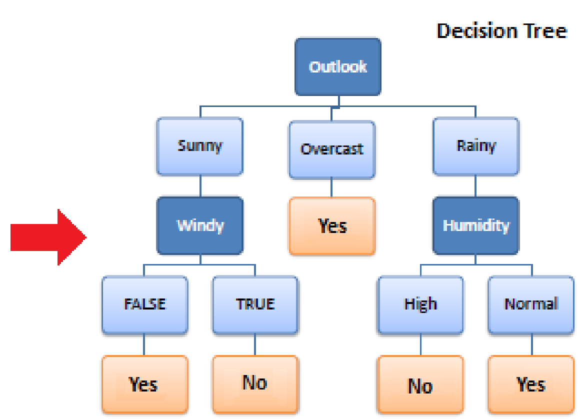
It uses a flowchart like a tree structure to show the predictions that result from a series of feature-based splits. It starts with a root node and ends with a decision made by leaves.[1]



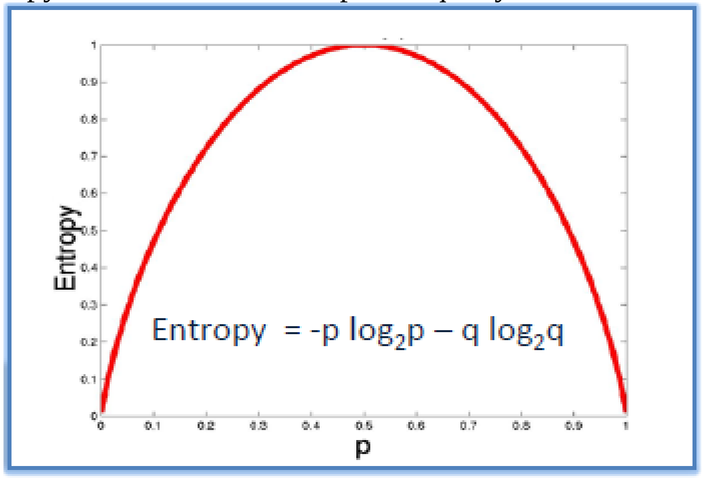
Root Nodes – It is the node present at the beginning of a decision tree. from this node the population starts dividing according to various features.
Decision Nodes – the nodes we get after splitting the root nodes are called Decision Node
Leaf Nodes – the nodes where further splitting is not possible are called leaf nodes or terminal nodes
Sub-tree – just like a small portion of a graph is called sub-graph similarly a sub-section of this decision tree is called sub-tree.
Pruning – It is cutting down some nodes to stop overfitting.

Predictors Target

Outlook	Temp.	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No



Entropy:
Entropy is used to calculate the homogeneity of a sample. If the sample is completely homogeneous the entropy is zero and if the sample is equally divided it has entropy of one.



$$\text{Entropy} = -0.5 \log_2 0.5 - 0.5 \log_2 0.5 = 1$$

a) Entropy using the frequency table of one attribute:

$$E(S) = \sum_{i=1}^{c} - p_i \log_2 p_i$$

Play Golf	
Yes	No
9	5

Entropy(PlayGolf) = Entropy (5,9)
= Entropy (0.36, 0.64)
= - (0.36 $\log_2$ 0.36) - (0.64 $\log_2$ 0.64)
= 0.94

b) Entropy using the frequency table of two attributes:

$$E(T, X) = \sum_{c \in X} P(c) E(c)$$

		Play Golf		
		Yes	No	
Outlook	Sunny	3	2	5
	Overcast	4	0	4
	Rainy	2	3	5
				14

E(PlayGolf, Outlook) = **P**(Sunny)***E**(3,2) + **P**(Overcast)***E**(4,0) + **P**(Rainy)***E**(2,3)

= (5/14)*0.971 + (4/14)*0.0 + (5/14)*0.971

= 0.693

Information Gain

The information gain is based on the decrease in entropy after a dataset is split on an attribute. Constructing a decision tree is all about finding attributes that return the highest information gain (i.e., the most homogeneous branches).[2]

Step 1: Calculate entropy of the target.

Entropy(PlayGolf) = Entropy (5,9)

$= \text{Entropy}(0.36, 0.64)$

$= -(0.36 \log_2 0.36) - (0.64 \log_2 0.64)$

$= 0.94$

Step 2: The dataset is then split on the different attributes. The entropy for each branch is calculated. Then it is added proportionally, to get total entropy for the split. The resulting entropy is subtracted from the entropy before the split. The result is the Information Gain, or decrease in entropy.

		Play Golf	
		Yes	No
Outlook	Sunny	3	2
	Overcast	4	0
	Rainy	2	3
Gain = 0.247			

		Play Golf	
		Yes	No
Temp.	Hot	2	2
	Mild	4	2
	Cool	3	1
Gain = 0.029			

		Play Golf	
		Yes	No
Humidity	High	3	4
	Normal	6	1
Gain = 0.152			

		Play Golf	
		Yes	No
Windy	False	6	2
	True	3	3
Gain = 0.048			

$$Gain(T,X) = Entropy(T) - Entropy(T,X)$$

G(PlayGolf, Outlook) = **E**(PlayGolf) – **E**(PlayGolf, Outlook)

= 0.940 – 0.693 = 0.247

Step 3: Choose attribute with the largest information gain as the decision node, divide the dataset by its
branches and repeat the same process on every branch.

		Play Golf	
		Yes	No
Outlook	Sunny	3	2
	Overcast	4	0
	Rainy	2	3
Gain = 0.247			

Outlook

Sunny

Outlook	Temp	Humidity	Windy	Play Golf
Sunny	Mild	High	FALSE	Yes
Sunny	Cool	Normal	FALSE	Yes
Sunny	Cool	Normal	TRUE	No
Sunny	Mild	Normal	FALSE	Yes
Sunny	Mild	High	TRUE	No

Overcast

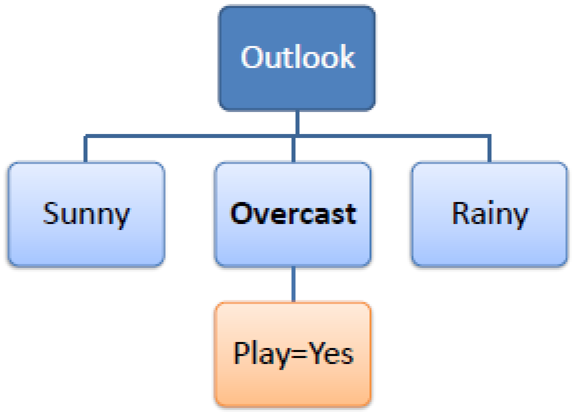
Overcast	Hot	High	FALSE	Yes
Overcast	Cool	Normal	TRUE	Yes
Overcast	Mild	High	TRUE	Yes
Overcast	Hot	Normal	FALSE	Yes

Rainy

Rainy	Hot	High	FALSE	No
Rainy	Hot	High	TRUE	No
Rainy	Mild	High	FALSE	No
Rainy	Cool	Normal	FALSE	Yes
Rainy	Mild	Normal	TRUE	Yes

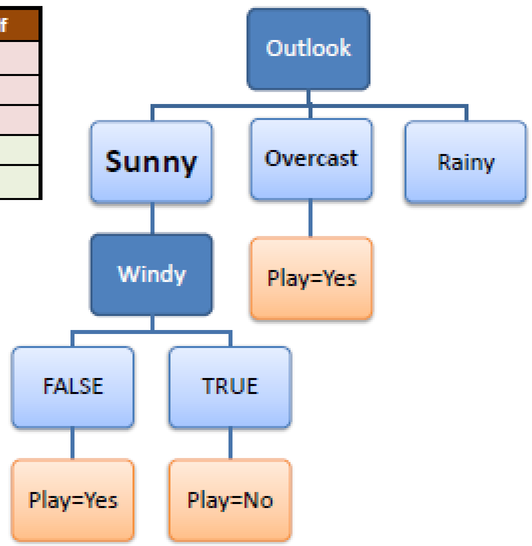
Step 4a: A branch with entropy of 0 is a leaf node.

Temp.	Humidity	Windy	Play Golf
Hot	High	FALSE	Yes
Cool	Normal	TRUE	Yes
Mild	High	TRUE	Yes
Hot	Normal	FALSE	Yes



Step 4b: A branch with entropy more than 0 needs further splitting.

Temp.	Humidity	Windy	Play Golf
Mild	High	FALSE	Yes
Cool	Normal	FALSE	Yes
Mild	Normal	FALSE	Yes
Cool	Normal	TRUE	No
Mild	High	TRUE	No



Step 5: The ID3 algorithm is run recursively on the non-leaf branches, until all data is classified.

Decision Tree to Decision Rules

A decision tree can easily be transformed to a set of rules by mapping from the root node to the leaf nodes one by one.

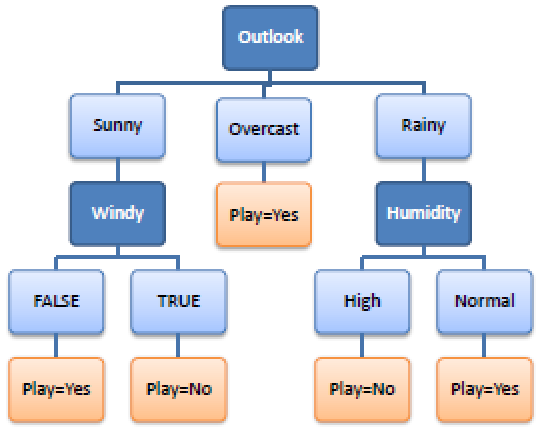
R_1: IF (Outlook=Sunny) AND (Windy=FALSE) THEN Play=Yes

R_2: IF (Outlook=Sunny) AND (Windy=TRUE) THEN Play=No

R_3: IF (Outlook=Overcast) THEN Play=Yes

R_4: IF (Outlook=Rainy) AND (Humidity=High) THEN Play=No

R_5: IF (Outlook=Rain) AND (Humidity=Normal) THEN Play=Yes



Pruning:
It is another method that can help us avoid overfitting. It helps in improving the performance of the tree by cutting the nodes or sub-nodes which are not significant. It removes the branches which have very low importance.
There are mainly 2 ways for pruning:
(i) **Pre-pruning** – we can stop growing the tree earlier, which means we can prune/remove/cut a node if it has low importance **while growing** the tree.
(ii) **Post-pruning** – once our **tree is built to its depth**, we can start pruning the nodes based on their significance.

Implementation:

Importing all the necessary libraries

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
```

Importing the csv file

```
df = pd.read_csv('../input/Admission_Predict.csv')
```

 # Check null values in the dataset

```
df.isnull().sum()
```

Out[ ]:
Serial No. 0
GRE Score 0
TOEFL Score 0
University Rating 0
SOP 0

LOR   0
CGPA   0
Research   0
Chance of Admit   0
dtype: int64

```
df.columns
```

Index(['Serial No.', 'GRE Score', 'TOEFL Score', 'University Rating', 'SOP',
'LOR ', 'CGPA', 'Research', 'Chance of Admit '],
dtype='object')

Updating chance of admission column
if chance >= 80% CHANCE = 1
if chance < 80% CHANCE = 0

```
dataset.loc[dataset['Chance of Admit '] < 0.8, 'Chance of Admit '] = 0
dataset.loc[dataset['Chance of Admit '] >= 0.8, 'Chance of Admit '] = 1
```

Initializing the variables

```
X = df.drop(['Chance of Admit ','Serial No.'],axis=1)
y = df['Chance of Admit ']
```

Split the data into training and testing set

```
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test =
train_test_split(X,y,test_size=0.25,random_state=123)
```

```
# importing required libraries
from sklearn.tree import DecisionTreeClassifier
from sklearn import metrics

# Creating Decision Tree classifer object
clf = DecisionTreeClassifier()

# Training Decision Tree Classifer
clf = clf.fit(X_train, Y_train)

#Predicting for the test data
y_pred = clf.predict(X_test)

Confusion matrix:

print("confusion matrix:\n")
print(metrics.confusion_matrix(Y_test, y_pred))
```

```
confusion matrix:
```

```
[[79  3]
 [ 4 39]]
```

```
print("1. Accuracy Score:", metrics.accuracy_score(Y_test, y_pred))

print("2. Precision Score:",metrics.precision_score(Y_test, y_pred))

print("3. Recall Score:", metrics.recall_score(Y_test, y_pred))

print("4. f1 Score:", metrics.f1_score(Y_test, y_pred))
```

```
1. Accuracy Score: 0.944
2. Precision Score: 0.9285714285714286
3. Recall Score: 0.9069767441860465
4. f1 Score: 0.9176470588235294
```

Application:

Helpful in solving classification problems.

References:

[1]Anshul Saini ,Analytics Vidhya,Decision Tree Algorithm – A Complete Guide
[2]Dr. Saed Sayad,https://www.saedsayad.com/decision_tree.htm

Assignment No -4

Assignment No -4

Title: E-mail Classification using Naïve-Bayes Algorithm.

Problem Statement:

A SMS unsolicited mail (every now and then known as cell smartphone junk mail) is any junk message brought to a cellular phone as textual content messaging via the Short Message Service (SMS). Use probabilistic approach (Naive Bayes Classifier / Bayesian Network) to implement SMS Spam Filtering system. SMS messages are categorized as SPAM or HAM using features like length of message, word depend, unique keywords etc.

Download Data -Set from:

https://www.kaggle.com/datasets/uciml/sms-spam-collection-dataset

This dataset is composed by just one text file, where each line has the correct class followed by the raw message.

I Apply Data pre-processing (Label Encoding, Data Transformation....) techniques if necessary
II Perform data-preparation (Train-Test Split)
III Apply at least two Machine Learning Algorithms and Evaluate Models
IV Apply Cross-Validation and Evaluate Models and compare performance.
V Apply Hyper parameter tuning and evaluate models and compare performance.

Objective: This assignment will help the students to realize how the Naïve Bayes algorithm works in classification of text.

S/W Packages and H/W apparatus used:

Linux OS: Ubuntu/Windows , Jupyter notebook.
PC with the configuration as Pentium IV 1.7 GHz. 128M.B RAM, 40 G.B HDD, 15''Color Monitor, Keyboard, Mouse

References:

1. Ethem Alpaydin, Introduction to Machine Learning, PHI 2nd Edition,2013.
2. Peter Flach: Machine Learning: The Art and Science of Algorithms that Make Sense of Data, Cambridge University Press, Edition 2012.

Theory:

Naive Bayes classifiers are a collection of classification algorithms based on **Bayes' Theorem**. It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e. every pair of features being classified is independent of each other.

To start with, let us consider a dataset.

Consider a fictional dataset that describes the weather conditions for playing a game of golf. Given the weather conditions, each tuple classifies the conditions as fit("Yes") or unfit("No") for playing golf.

Here is a tabular representation of our dataset.

	Outlook	Temperature	Humidity	Windy	Play Golf
0	Rainy	Hot	High	False	No
1	Rainy	Hot	High	True	No
2	Overcast	Hot	High	False	Yes
3	Sunny	Mild	High	False	Yes
4	Sunny	Cool	Normal	False	Yes
5	Sunny	Cool	Normal	True	No
6	Overcast	Cool	Normal	True	Yes
7	Rainy	Mild	High	False	No

	Outlook	Temperature	Humidity	Windy	Play Golf
8	Rainy	Cool	Normal	False	Yes
9	Sunny	Mild	Normal	False	Yes
10	Rainy	Mild	Normal	True	Yes
11	Overcast	Mild	High	True	Yes
12	Overcast	Hot	Normal	False	Yes
13	Sunny	Mild	High	True	No

The dataset is divided into two parts, namely, **feature matrix** and the **response vector**.

- Feature matrix contains all the vectors(rows) of dataset in which each vector consists of the value of **dependent features**. In above dataset, features are ‘Outlook’, ‘Temperature’, ‘Humidity’ and ‘Windy’.
- Response vector contains the value of **class variable** (prediction or output) for each row of feature matrix. In above dataset, the class variable name is ‘Play golf’.

Assumption:

The fundamental Naive Bayes assumption is that each feature makes an:

- independent
- equal

contribution to the outcome.

With relation to our dataset, this concept can be understood as:

- We assume that no pair of features are dependent. For example, the temperature being ‘Hot’ has nothing to do with the humidity or the outlook being ‘Rainy’ has no effect on the winds. Hence, the features are assumed to be **independent**.
- Secondly, each feature is given the same weight(or importance). For example, knowing only temperature and humidity alone can’t predict the outcome accurately. None of the attributes is irrelevant and assumed to be contributing **equally** to the outcome.

Note: The assumptions made by Naive Bayes are not generally correct in real-world situations. In-fact, the independence assumption is never correct but often works well in practice.

Now, before moving to the formula for Naive Bayes, it is important to know about Bayes' theorem.

Bayes' Theorem

Bayes' theorem is a way to figure out conditional probability. Conditional probability is the probability of an event happening, given that it has some relationship to one or more other events. For example, your probability of getting a parking space is connected to the time of day you park, where you park, and what conventions are going on at any time. Bayes' theorem is slightly more nuanced. In a nutshell, it gives you the actual probability of an **event** given information about **tests**.

- "Events" Are different from "tests." For example, there is a **test** for liver disease, but that's separate from the **event** of actually having liver disease.
- **Tests are flawed**: just because you have a positive test does not mean you actually have the disease. Many tests have a high false positive rate. **Rare events tend to have higher false positive rates** than more common events. We're not just talking about medical tests here. For example, spam filtering can have high false positive rates. Bayes' theorem takes the test results and calculates your *real probability* that the test has identified the event.

The Formula

Bayes' Theorem (also known as Bayes' rule) is a deceptively simple formula used to calculate conditional probability. The Theorem was named after English mathematician Thomas Bayes (1701-1761). The formal definition for the rule is:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

In most cases, you can't just plug numbers into an equation; You have to figure out what your "tests" and "events" are first. For two events, A and B, Bayes' theorem allows you to figure out p(A|B) (the probability that event A happened, given that test B was positive) from p(B|A) (the probability that test B happened, given that event A happened). It can be a little tricky to wrap your head around as technically you're working backwards; you may have to switch your tests and events around, which can get confusing. An example should clarify what I mean by "switch the tests and events around."

Bayes' Theorem Example #1

You might be interested in finding out a patient's probability of having liver disease if they are an alcoholic. "Being an alcoholic" is the **test** (kind of like a litmus test) for liver disease.

- **A** could mean the event “Patient has liver disease.” Past data tells you that 10% of patients entering your clinic have liver disease. P(A) = 0.10.
- **B** could mean the litmus test that “Patient is an alcoholic.” Five percent of the clinic’s patients are alcoholics. P(B) = 0.05.
- You might also know that among those patients diagnosed with liver disease, 7% are alcoholics. This is your **B|A:** the probability that a patient is alcoholic, given that they have liver disease, is 7%.

Bayes’ theorem tells you:
P(A|B) = (0.07 * 0.1)/0.05 = 0.14
In other words, if the patient is an alcoholic, their chances of having liver disease is 0.14 (14%). This is a large increase from the 10% suggested by past data. But it’s still unlikely that any particular patient has liver disease.

More Bayes’ Theorem Examples

Bayes’ Theorem Problems Example #2

Another way to look at the theorem is to say that one event follows another. Above I said “tests” and “events”, but it’s also legitimate to think of it as the “first event” that leads to the “second event.” There’s no one right way to do this: use the terminology that makes most sense to you.

In a particular pain clinic, 10% of patients are prescribed narcotic pain killers. Overall, five percent of the clinic’s patients are addicted to narcotics (including pain killers and illegal substances). Out of all the people prescribed pain pills, 8% are addicts. *If a patient is an addict, what is the probability that they will be prescribed pain pills?*

Step 1: **Figure out what your event “A” is from the question.** That information is in the italicized part of this particular question. The event that happens first (A) is being prescribed pain pills. That’s given as 10%.

Step 2: **Figure out what your event “B” is from the question.** That information is also in the italicized part of this particular question. Event B is being an addict. That’s given as 5%.

Step 3: **Figure out what the probability of event B (Step 2) given event A (Step 1)**. In other words, find what (B|A) is. We want to know “Given that people are prescribed pain pills, what’s the probability they are an addict?” That is given in the question as 8%, or .8.

Step 4: **Insert your answers from Steps 1, 2 and 3 into the formula and solve.** P(A|B) = P(B|A) * P(A) / P(B) = (0.08 * 0.1)/0.05 = 0.16

The probability of an addict being prescribed pain pills is 0.16 (16%).

Example #3: the Medical Test

A slightly more complicated example involves a medical test (in this case, a genetic test):

There are **several forms of Bayes' Theorem** out there, and they are all equivalent (they are just written in slightly different ways). In this next equation, "X" is used in place of "B." In addition, you'll see some changes in the denominator. The proof of why we can rearrange the equation like this is beyond the scope of this article (otherwise it would be 5,000 words instead of 2,000!). However, if you come across a question involving medical tests, you'll likely be using this alternative formula to find the answer:

$$\Pr(\mathrm{A}|\mathrm{X}) = \frac{\Pr(\mathrm{X}|\mathrm{A})\Pr(\mathrm{A})}{\Pr(\mathrm{X}|\mathrm{A})\Pr(A) + \Pr(\mathrm{X}|\sim \mathrm{A})\Pr(\sim A)}$$

Bayes Theorem Examples

1% of people have a certain genetic defect.
90% of tests for the gene detect the defect (true positives).
9.6% of the tests are false positives.
If a person gets a positive test result, **what are the odds they actually have the genetic defect?**

The first step into solving Bayes' theorem problems is to assign letters to events:

- A = chance of having the faulty gene. That was given in the question as 1%. That also means the probability of *not* having the gene (~A) is 99%.
- X = A positive test result.

So:

1. P(A|X) = Probability of having the gene given a positive test result.
2. P(X|A) = Chance of a positive test result given that the person actually has the gene. That was given in the question as 90%.
3. p(X|~A) = Chance of a positive test if the person *doesn't* have the gene. That was given in the question as 9.6%

Now we have all of the information we need to put into the equation: P(A|X) = (.9 * .01) / (.9 * .01 + .096 * .99) = 0.0865 (8.65%).

The probability of having the faulty gene on the test is 8.65%.

Bayes' Theorem Problems #4: A Test for Cancer

I wrote about how challenging physicians find probability and statistics in my post on reading mammogram results wrong. It's not surprising that physicians are way off with their interpretation of results, given that some tricky probabilities are at play. Here's a second example of how Bayes'

Theorem works. I've used similar numbers, but the question is worded differently to give you another opportunity to wrap your mind around how you decide which is event A and which is event X.

Q. Given the following statistics, what is the probability that a woman has cancer if she has a positive mammogram result?

- One percent of women over 50 have breast cancer.
- Ninety percent of women who have breast cancer test positive on mammograms.
- Eight percent of women will have false positives.

Step 1: Assign events to A or X. You want to know what a woman's probability of having cancer is, given a positive mammogram. For this problem, actually having cancer is A and a positive test result is X.
Step 2: List out the parts of the equation (this makes it easier to work the actual equation):
P(A)=0.01
P(~A)=0.99
P(X|A)=0.9
P(X|~A)=0.08
Step 3: Insert the parts into the equation and solve. Note that as this is a medical test, we're using the form of the equation from example #2:
(0.9 * 0.01) / ((0.9 * 0.01) + (0.08 * 0.99) = 0.10.

The probability of a woman having cancer, given a positive test result, is 10%.

Remember when (up there ^^) I said that there are many equivalent ways to write Bayes Theorem? Here is another equation, that you can use to figure out the above problem. You'll get exactly the same result:

$$P(B|A) = \frac{P(B \cap A)}{P(A)} = \frac{P(B \cap A)}{P(B \cap A) + P(B^c \cap A)}$$

The main difference with this form of the equation is that it uses the probability terms *intersection*(∩) and *complement* (^{c}). Think of it as shorthand: it's the same equation, written in a different way.

In order to find the probabilities on the right side of this equation, use the multiplication rule:

P(B ∩ A) = P(B) * P(A|B)

The two sides of the equation are equivalent, and P(B) * P(A|B) is what we were using when we solved the numerator in the problem above.
P(B) * P(A|B) = 0.01 * 0.9 = 0.009

For the denominator, we have $P(B^c \cap A)$ as part of the equation. This can be (equivalently) rewritten as $P(B^c*P(A|B^c)$. This gives us:
$P(B^c*P(A|B^c) = 0.99 * 0.08 = 0.0792$.

Inserting those two solutions into the formula, we get:
0.009 / (0.009 + 0.0792) = 10%.

Bayes' Theorem Problems: Another Way to Look at It.

Bayes' theorem problems can be figured out *without* using the equation (although using the equation is probably simpler). But if you can't wrap your head around why the equation works (or what it's doing), here's the non-equation solution for the same problem in #1 (the genetic test problem) above.

Step 1: Find the probability of a true positive on the test. That equals people who actually have the defect (1%) * true positive results (90%) = .009.

Step 2: Find the probability of a false positive on the test. That equals people who don't have the defect (99%) * false positive results (9.6%) = .09504.

Step 3: Figure out the probability of getting a positive result on the test. That equals the chance of a true positive (Step 1) plus a false positive (Step 2) = .009 + .09504 = .0.10404.

Step 4: Find the probability of actually having the gene, given a positive result. Divide the chance of having a real, positive result (Step 1) by the chance of getting any kind of positive result (Step 3) = .009/.10404 = 0.0865 (8.65%).

Other forms of Bayes' Theorem

Bayes' Theorem has several forms. You probably won't encounter any of these other forms in an elementary stats class. The different forms can be used for different purposes. For example, one version uses what Rudolf Carnap called the "**probability ratio**". The probability ratio rule states that any event (like a patient having liver disease) must be multiplied by this factor $PR(H,E)=P_E(H)/P(H)$. That gives the event's probability conditional on E. The **Odds Ratio**

Rule is very similar to the probability ratio, but the likelihood ratio divides a test's true positive rate divided by its false positive rate. The formal definition of the Odds Ratio rule is $OR(H,E)=P_{H,}(E)/P_{\sim H}(E)$.

Bayesian Spam Filtering

Although Bayes' Theorem is used extensively in the medical sciences, there are other applications. For example, it's used to filter spam. The **event** in this case is that the message is spam. The **test** for spam is that the message contains some flagged words (like "viagra" or "you have won"). Here's the equation set up (from Wikipedia), read as "The probability a message is spam given that it contains certain flagged words":

$$\Pr(\text{spam}|\text{words}) = \frac{\Pr(\text{words}|\text{spam})\Pr(\text{spam})}{\Pr(\text{words})}$$

The actual equations used for spam filtering are a little more complex; they contain more flags than just content. For example, the timing of the message, or how often the filter has seen the same content before, are two other spam tests.

Implementation

In [70]:
```python
import pandas as pd
```

In [71]:
```python
df = pd.read_csv('Email_Spam.csv')
df.head()
```

Out[71]:

	Category	Message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

In [72]:
```python
df.groupby('Category').describe()
```

Out[72]:

	Message			
	count	unique	top	freq
Category				
ham	4825	4516	Sorry, I'll call later	30
spam	747	641	Please call our customer service representativ...	4

In [73]:
```python
df['spam']=df['Category'].apply(lambda x: 1 if x=='spam' else 0)
df.head()
```

Out[73]:

	Category	Message	spam
0	ham	Go until jurong point, crazy.. Available only ...	0
1	ham	Ok lar... Joking wif u oni...	0
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	1
3	ham	U dun say so early hor... U c already then say...	0
4	ham	Nah I don't think he goes to usf, he lives aro...	0

In [74]:
```python
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df.Message,df.spam)
```

In [75]:
```python
from sklearn.feature_extraction.text import CountVectorizer
v = CountVectorizer()
X_train_count = v.fit_transform(X_train.values)
X_train_count.toarray()[:2]
#print(v.get_feature_names())
```

Out[75]:
```
array([[0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0]], dtype=int64)
```

In [76]:
```python
from sklearn.naive_bayes import MultinomialNB
model = MultinomialNB()
model.fit(X_train_count,y_train)
```

Out[76]:
```
MultinomialNB()
```

In [77]:
```python
emails = [
    'How are you brother?',
    'Get Flat 50% on Your body outfits'
]
emails_count = v.transform(emails)
model.predict(emails_count)
```

Out[77]:
```
array([0, 0], dtype=int64)
```

In [78]:
```python
X_test_count = v.transform(X_test)
model.score(X_test_count, y_test)
```

Out[78]:
```
0.9877961234745154
```

Assignment No -5

Title: K Means Clustering

Problem Statement:

Perform following operations on given dataset:

a) Apply Data pre-processing (Label Encoding, Data Transformation....) techniques if necessary.
b) Perform data-preparation (Train-Test Split)
c) Apply Machine Learning Algorithm
d) Evaluate Model.
e) Apply Cross-Validation and Evaluate Model

Objective:

This assignment will help the students to realize how to do Clustering using K Means Clustering algorithm.

S/W Packages and H/W apparatus used:

Linux OS: Ubantu/Windows , Jupyter notebook.
PC with the configuration as Pentium IV 1.7 GHz. 128M.B RAM, 40 G.B HDD,
15''Color Monitor, Keyboard, Mouse

References:

3. *Ethem Alpaydin, Introduction to Machine Learning, PHI 2nd Edition,2013.*
4. *Peter Flach: Machine Learning: The Art and Science of Algorithms that Make Sense of Data,Cambridge University Press, Edition 2012..*

Theory:

Introduction to K-means Clustering

K-means clustering is a type of unsupervised learning, which is used when you have unlabeled data (i.e., data without defined categories or groups). The goal of this algorithm is to find groups in the data, with the number of groups represented by the variable K. [1]

The algorithm works iteratively to assign each data point to one of K groups based on the features that are provided. Data points are clustered based on feature similarity.

The results of the K-means clustering algorithm are:
1. The centroids of the K clusters, which can be used to label new data
2. Labels for the training data (each data point is assigned to a single cluster) Rather than defining groups before looking at the data, clustering allows you to find and analyze the groups that have formed organically.

The "Choosing K" section below describes how the number of groups can be determined. Each centroid of a cluster is a collection of feature values which define the resulting groups. Examining the centroid feature weights can be used to qualitatively interpret what kind of group each cluster represents.

This introduction to the K-means clustering algorithm covers:

Common business cases where K-means is used

The steps involved in running the algorithm

Some examples of use cases are:

Behavioral segmentation:
- o Segment by purchase history
- o Segment by activities on application, website, or platform.
- o Define personas based on interests
- o Create profiles based on activity monitoring

Inventory categorization:
- o Group inventory by sales activity
- o Group inventory by manufacturing metrics

Sorting sensor measurements:
- o Detect activity types in motion sensors o Group images
- o Separate audio o Identify groups in health monitoring

Detecting bots or anomalies:
- o Separate valid activity groups from bots
- o Group valid activity to clean up outlier detection In addition, monitoring if a tracked data point switches between groups over time can be used to detect meaningful changes in the data.

Algorithm:
The K-means clustering algorithm uses iterative refinement to produce a final result. The algorithm inputs are the number of clusters K and the data set. The data set is a collection of features for each data point. The algorithms start with initial estimates for the K centroids, which can either be randomly generated or randomly selected from the data set. The

algorithm then iterates between two steps:

1. **Data assignment step:**

   Each centroid defines one of the clusters. In this step, each data point is assigned to its nearest centroid, based on the squared Euclidean distance. More formally, if ci is the collection of centroids in set C, then each data point x is assigned to a cluster based on

   $$\underset{c_i \in C}{\operatorname{argmin}}\ dist(c_i, x)^2$$

   where dist(·) is the standard (L2) Euclidean distance. Let the set of data point assignments for each i th cluster centroid be Si .

2.**Centroid update step:**

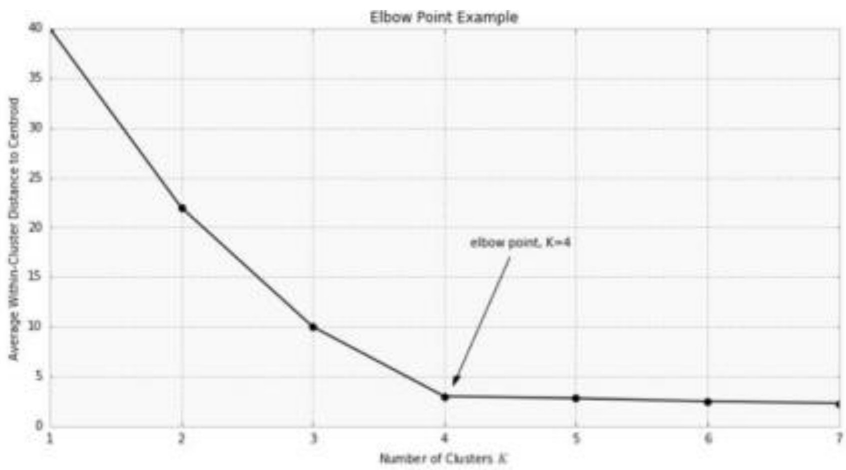
In this step, the centroids are recomputed. This is done by taking the mean of all data points assigned to that centroid's cluster.

$$c_i = \frac{1}{|S_i|}\sum_{x_i \in S_i} x_i$$

The algorithm iterates between steps one and two until a stopping criteria is met (i.e., no data points change clusters, the sum of the distances is minimized, or some maximum number of iterations is reached).
This algorithm is guaranteed to converge to a result. The result may be a local optimum (i.e. not necessarily the best possible outcome), meaning that assessing more than one run of the algorithm with randomized starting centroids may give a better outcome.

Choosing K

The algorithm described above finds the clusters and data set labels for a particular pre-chosen K. To find the number of clusters in the data, the user needs to run the K-means clustering algorithm for a range of K values and compare the results. In general, there is no method for determining exact value of K, but an accurate estimate can be obtained using the following techniques. One of the metrics that is commonly used to compare results across different values of K is the mean distance between data points and their cluster centroid. Since increasing the number of clusters will always reduce the distance to data points, increasing K will always decrease this metric, to the extreme of reaching zero when K is the same as the number of data points. Thus, this metric cannot be used as the sole target. Instead, mean distance to the centroid as a function of K is plotted and the "elbow point," where the rate of decrease sharply shifts, can be used to roughly determine K.
A number of other techniques exist for validating K, including cross-validation, information criteria, the information theoretic jump method, the silhouette method, and the G-means algorithm. In addition, monitoring the distribution of data points across groups provides insight into how the algorithm is splitting the data for each K.



Implementation:

Importing Dataset

from pandas import read_csv
A=read_csv("E:/DS1/Mall_Customers.csv")

Dropping the irrelevant columns

B=A.drop([“Customer_ID”],axis=1)

Label encoding

# Import label encoder
from sklearn import preprocessing

# label_encoder object knows how to understand word labels.
label_encoder = preprocessing.LabelEncoder()

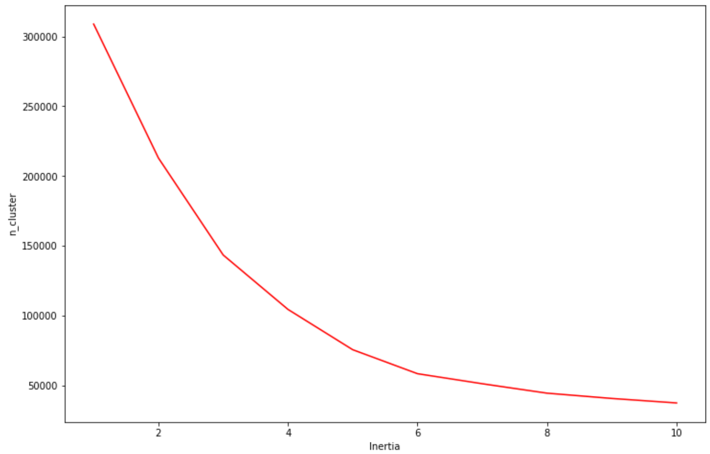
Encode labels in column 'species'.
B['Genre']= label_encoder.fit_transform(B['Genre'])

B['Genre'].unique()
`array([1, 0], dtype=int64)`

Finding K

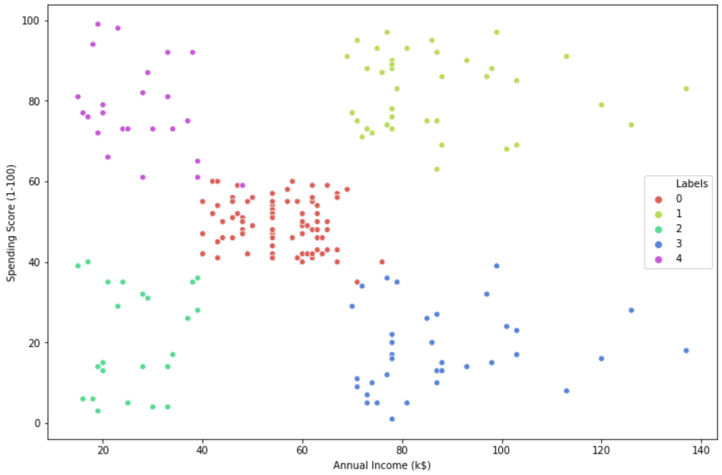
```
from sklearn.cluster import KMeans
cluster = []
for k in range (1, 11):
    kmean = KMeans(n_clusters=k).fit(B)
    cluster.append(kmean.inertia_)

import matplotlib.pyplot as plt
```

```
plt.figure(figsize=(12, 8))
plt.plot(range(1, 11), cluster, 'r-')
plt.xlabel('Inertia')
plt.ylabel('n_cluster')
plt.show()
```



With above value of K,Create K means clustering model

```
km = KMeans(n_clusters=5).fit(B)
B['Labels'] = km.labels_

import seaborn as sns
plt.figure(figsize=(12, 8))
sns.scatterplot(B['Annual Income (k$)'], B['Spending Score (1-100)'], hue=B['Labels'],
palette=sns.color_palette('hls', 5))
plt.show()
```



References:
[1]Andrea Trevino,Introduction to K-means Clustering ,Oracle AI & Data Science Blog

Assignment No -6

Title: Association Rule Learning

Problem Statement:

Download Market Basket Optimization dataset from below link.
Data Set: https://www.kaggle.com/hemanthkumar05/market-basket-optimization
This dataset comprises the list of transactions of a retail company over the period of one week. It contains a total of 7501 transaction records where each record consists of the list of items sold in one transaction. Using this record of transactions and items in each transaction, find the association rules between items.
There is no header in the dataset and the first row contains the first transaction, so mentioned header = None here while loading dataset.

a. Follow following steps :
b. Data Preprocessing
c. Generate the list of transactions from the dataset
d. Train Apriori algorithm on the dataset
e. Visualize the list of rules

Generated rules depend on the values of hyper parameters. By increasing the minimum confidence value and find the rules accordingly

Objective:

This assignment will help the students to understand and implement Apriori Algorithm.

S/W Packages and H/W apparatus used:

Linux OS: Ubantu/Windows , Jupyter notebook.
PC with the configuration as Pentium IV 1.7 GHz. 128M.B RAM, 40 G.B HDD, 15''Color Monitor, Keyboard, Mouse

References:

1.Ethem Alpaydin, Introduction to Machine Learning, PHI 2nd Edition,2013.
2. Peter Flach: Machine Learning: The Art and Science of Algorithms that Make Sense of Data,Cambridge University Press, Edition 2012.

Theory:

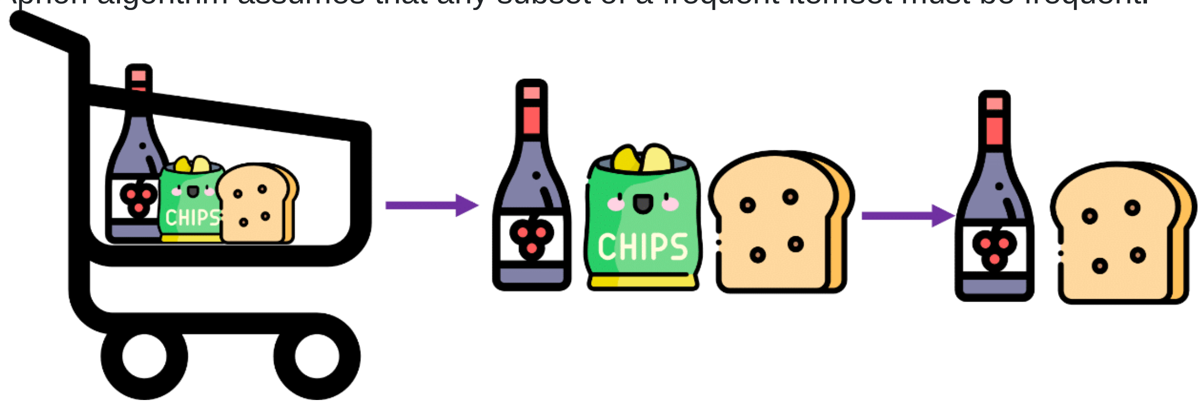
the Apriori algorithm is used for the purpose of association rule mining.Association rule mining is a technique to identify frequent patterns and associations among a set of items.

For example, understanding customer buying habits. By finding correlations and associations between different items that customers place in their 'shopping basket,' recurring patterns can be derived.

This process of identifying an association between products/items is called association rule mining. To implement association rule mining, many algorithms have been developed. Apriori algorithm is one of the most popular and arguably the most efficient algorithms among them.

Apriori Algorithm

Apriori algorithm assumes that any subset of a frequent itemset must be frequent.



Say, a transaction containing {wine, chips, bread} also contains {wine, bread}. So, according to the principle of Apriori, if {wine, chips, bread} is frequent, then {wine, bread} must also be frequent.

The key concept in the Apriori algorithm is that it assumes all subsets of a frequent itemset to be frequent. Similarly, for any infrequent itemset, all its supersets must also be infrequent.

Here is a dataset consisting of six transactions in an hour. Each transaction is a combination of 0s and 1s, where 0 represents the absence of an item and 1 represents the presence of it.

Here is a dataset consisting of six transactions in an hour. Each transaction is a combination of 0s and 1s, where 0 represents the absence of an item and 1 represents the presence of it.

Transaction ID	Wine	Chips	Bread	Milk

1	1	1	1	1
2	1	0	1	1
3	0	0	1	1
4	0	1	0	0
5	1	1	1	1
6	1	1	0	1

We can find multiple rules from this scenario. For example, in a transaction of wine, chips, and bread, if wine and chips are bought, then customers also buy bread.

{wine, chips} =>; {bread}

In order to select the interesting rules out of multiple possible rules from this small business scenario, we will be using the following measures:

- Support
- Confidence
- List
- Conviction

Support

Support of item *x* is nothing but the ratio of the number of transactions in which item *x* appears to the total number of transactions.

i.e.,

Support(wine) = $\frac{\textit{Number of transactions in which the item wine appears}}{\textit{Total number of transactions}}$

Support(wine) = 4/6= 0.66667

Confidence

Confidence (*x* => *y*) signifies the likelihood of the item *y* being purchased when item *x* is purchased. This method takes into account the popularity of item *x*.

i.e.,

Conf({wine, chips} => {bread}) = $\frac{support(wine,chips,bread)}{support(wine,chips)}$

Conf({wine, chips} => {bread})= $\frac{\frac{2}{6}}{\frac{3}{6}}$ = 0.667

Lift

Lift (*x* => *y*) is nothing but the ‘interestingness’ or the likelihood of the item *y* being purchased when item *x* is sold. Unlike confidence (*x* => *y*), this method takes into account the popularity of the item *y*.

i.e.,

lift ({wine, chips} => {bread}) = $\frac{support(wine,chips,bread)}{support(wine,chips)}$

lift ({wine, chips} => {bread}) = $\frac{\frac{2}{6}}{\frac{3}{6}*\frac{4}{6}}$ =1

- Lift (*x* => *y*) = 1 means that there is no correlation within the itemset.
- Lift (*x* => *y*) > 1 means that there is a positive correlation within the itemset, i.e., products in the itemset, *x* and *y*, are more likely to be bought together.
- Lift (*x* => *y*) < 1 means that there is a negative correlation within the itemset, i.e., products in itemset, *x* and *y*, are unlikely to be bought together.

Dataset

Below is the transaction data from Day 1. This dataset contains 6 items and 22 transaction records.

	A	B	C	D	E	F
1	Wine	Chips	Bread	Butter	Milk	Apple
2	Wine		Bread	Butter	Milk	
3			Bread	Butter	Milk	
4		Chips				Apple
5	Wine	Chips	Bread	Butter	Milk	Apple
6	Wine	Chips			Milk	
7	Wine	Chips	Bread	Butter		Apple
8	Wine	Chips			Milk	
9	Wine		Bread			Apple
10	Wine		Bread	Butter	Milk	
11		Chips	Bread	Butter		Apple
12	Wine			Butter	Milk	Apple
13	Wine	Chips	Bread	Butter	Milk	
14	Wine		Bread		Milk	Apple
15	Wine		Bread	Butter	Milk	Apple
16	Wine	Chips	Bread	Butter	Milk	Apple
17		Chips	Bread	Butter	Milk	Apple
18		Chips		Butter	Milk	Apple
19	Wine	Chips	Bread	Butter	Milk	Apple
20	Wine		Bread	Butter	Milk	Apple
21	Wine	Chips	Bread		Milk	Apple
22		Chips				

Environment Setup:

Before we move forward, we need to install the ‘apyori’ package first.

```
pip install apyori
```

Market Basket Analysis Implementation within Python

With the help of the apyori package, we will be implementing the Apriori algorithm in order to help the manager in market basket analysis.

Step 1: Import the libraries

```
In [1]: #Importing the required datasets
        import numpy as np
        import pandas as pd
        from apyori import apriori
```

Step 2: Load the dataset

```
In [2]: #Loading the dataset
        store_data = pd.read_csv('Day1.csv', header=None)
```

Step 3: Have a glance at the records

```
In [3]: #Having a glance at the records
        store_data
```

out[3]:

	0	1	2	3	4	5
0	Wine	Chips	Bread	Butter	Milk	Apple
1	Wine	NaN	Bread	Butter	Milk	NaN
2	NaN	NaN	Bread	Butter	Milk	NaN
3	NaN	Chips	NaN	NaN	NaN	Apple
4	Wine	Chips	Bread	Butter	Milk	Apple
5	Wine	Chips	NaN	NaN	Milk	NaN
6	Wine	Chips	Bread	Butter	NaN	Apple
7	Wine	Chips	NaN	NaN	Milk	NaN
8	Wine	NaN	Bread	NaN	NaN	Apple
9	Wine	NaN	Bread	Butter	Milk	NaN
10	NaN	Chips	Bread	Butter	NaN	Apple
11	Wine	NaN	NaN	Butter	Milk	Apple
12	Wine	Chips	Bread	Butter	Milk	NaN
13	Wine	NaN	Bread	NaN	Milk	Apple
14	Wine	NaN	Bread	Butter	Milk	Apple
15	Wine	Chips	Bread	Butter	Milk	Apple
16	NaN	Chips	Bread	Butter	Milk	Apple
17	NaN	Chips	NaN	Butter	Milk	Apple
18	Wine	Chips	Bread	Butter	Milk	Apple
19	Wine	NaN	Bread	Butter	Milk	Apple
20	Wine	Chips	Bread	NaN	Milk	Apple
21	NaN	Chips	NaN	NaN	NaN	NaN

Step 4 :Convert Pandas DataFrame into a list of lists

```
In [5]: #Converting the pandas dataframe into a list of lists
        records = []
        for i in range(0, 22):
            records.append([str(store_data.values[i,j]) for j in range(0, 6)])
```

Step 5: Build the Apriori model

```
In [7]: #Building the first apriori model
        association_rules = apriori(records, min_support=0.50, min_confidence=0.7, min_lift=1.2, min_length=2)
        association_results = list(association_rules)
```

Step 6: Print out the number of rules

```
In [8]: #Getting the number of rules
        print(len(association_results))
```

Step 7: Have a glance at the rule

```
In [10]: #Glancing at the first rule
         print(association_results)
```

```
[RelationRecord(items=frozenset({'Milk', 'Butter', 'Bread'}), support=0.5, ordered_statistics=[OrderedStatistic(items_base=froz
enset({'Milk', 'Bread'}), items_add=frozenset({'Butter'}), confidence=0.8461538461538461, lift=1.241025641025641)])]
```

The support value for the first rule is 0.5. This number is calculated by dividing the number of transactions containing 'Milk,' 'Bread,' and 'Butter' by the total number of transactions.

The confidence level for the rule is 0.846, which shows that out of all the transactions that contain both "Milk" and "Bread", 84.6 % contain 'Butter' too.

The lift of 1.241 tells us that 'Butter' is 1.241 times more likely to be bought by the customers who buy both 'Milk' and 'Butter' compared to the default likelihood sale of 'Butter.'

Conclusion :

Apriori algorithm is implemented

ADBMS

Assignment: 1

AIM:

Create a database with suitable example using MongoDB and implement

1. Inserting and saving document (batch insert, insert validation)
2. Removing document
3. Updating document (document replacement, using modifiers, up inserts, updating multiple documents, returning updated documents)
4. Execute at least 10 queries on any suitable MongoDB database that demonstrates following:
    - Find and find One (specific values)
    - Query criteria (Query conditionals, OR queries, $not, Conditional semantics)
    - Type-specific queries (Null, Regular expression, Querying arrays) where queries
    - Cursors (Limit, skip, sort, advanced query options)

PROBLEM STATEMENT /DEFINITION

Create a database with suitable example using MongoDB and implement

- Inserting and saving document (batch insert, insert validation)
- Removing document
- Updating document (document replacement, using modifiers, upserts, updating multiple documents, returning updated documents)

OBJECTIVE:

To understand Mongodb basic commands
To implement the concept of document oriented databases.
To understand Mongodb retrieval commands

THEORY:

SQL VsMongoDB

SQL Concepts	MongoDB Concepts
Database	**Database**

Table	**Collection**
Row	**Document 0r BSON Document**
Column	**Field**
Index	**Index**
Table Join	**Embedded Documents & Linking**
Primary Key	**Primary Key**
Specify Any Unique Column Or Column Combination As Primary Key.	**In Mongodb, The Primary Key Is Automatically Set To The _Id Field.**
Aggregation (E.G. Group By)	**Aggregation Pipeline**

1.Create a collection in mongodb

db.createCollection(“Teacher_info")

2.Create a capped collection in mongodb

>db.createCollection("audit", {capped:true, size:20480})

{ "ok" : 1 }

3.Insert a document into collection

db.Teacher_info.insert({ Teacher_id: “Pic001", Teacher_Name: “Ravi",Dept_Name: “IT”, Sal:30000, status: "A" })

db.Teacher_info.insert({ Teacher_id: “Pic002", Teacher_Name: “Ravi",Dept_Name: “IT”, Sal:20000, status: "A" })

db.Teacher_info.insert({ Teacher_id: “Pic003", Teacher_Name: “Akshay",Dept_Name: “Comp”, Sal:25000, status: “N" })

4.Update a document into collection

```
db. Teacher_info.update( { sal: { $gt: 25000 } }, { $set: { Dept_name: “ETC" } }, {
multi: true } )

db. Teacher_info.update( { status: "A" } , { $inc: { sal: 10000 } }, { multi: true } )
```

5.Remove a document from collection

```
db.Teacher_info.remove({Teacher_id: "pic001"});
db. Teacher_info.remove({})
```

6.Alter a field into a mongodb document

```
db.Teacher_info.update( { }, { $set: { join_date: new Date() } }, { multi: true} )
```

7.To drop a particular collection

```
db.Teacher_info.drop()
```

Retrieval From Database:-

When we retrieve a document from mongodb collection it always add a _id field in the every document which conatin unique _id field.

ObjectId(<hexadecimal>)

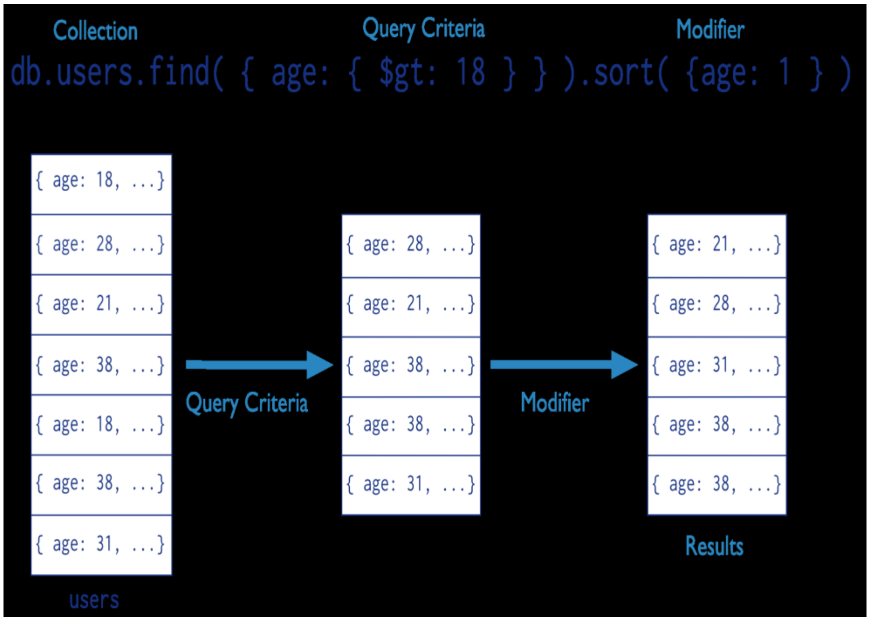
Returns a new ObjectId value. The 12-byte ObjectId value consists of:

4-byte value representing the seconds since the Unix epoch,

3-byte machine identifier,

2-byte process id, and

3-byte counter,starting with a random value.



1. Retrieve a collection in mongodb using Find command

db.Teacher.find()

```
{ "_id" : 101, "Name" : "Dev",
"Address" : [  {  "City" : "Pune",  "Pin" : 444043 } ],
"Department" : [  {  "Dept_id" : 111,  "Dept_name" : "IT" } ],
 "Salary" : 78000 }

{ "_id" : 135, "Name" : "Jennifer", "Address" : [  {  "City" :
"Mumbai",  "Pin" : 444111 } ], "Department" : [  {  "Dept_id" : 112,
"Dept_name" : "COMP" } ], "Salary" : 65000 }
{ "_id" : 126, "Name" : "Gaurav", "Address" : [  {  "City" : "Nashik",
"Pin" : 444198 } ], "Department" : [  {  "Dept_id" : 112,  "Dept_name"
: "COMP" } ], "Salary" : 90000 }
{ "_id" : 175, "Name" : "Shree", "Address" : [  {  "City" : "Nagpur",
"Pin" : 444158 } ], "Department" : [  {  "Dept_id" : 113,  "Dept_name"
: "ENTC" } ], "Salary" : 42000 }
{ "_id" : 587, "Name" : "Raman", "Address" : [  {  "City" : "Banglore",
"Pin" : 445754 } ], "Department" : [  {  "Dept_id" : 113,  "Dept_name"
: "ENTC" } ], "Salary" : 79000 }
{ "_id" : 674, "Name" : "Mandar", "Address" : [  {  "City" : "Jalgaon",
"Pin" : 465487 } ], "Department" : [  {  "Dept_id" : 111,  "Dept_name"
: "IT" } ], "Salary" : 88000 }
{ "_id" : 573, "Name" : "Manish", "Address" : [  {  "City" : "Washim",
"Pin" : 547353 } ], "Department" : [  {  "Dept_id" : 112,  "Dept_name"
: "COMP" } ], "Salary" : 65000 }
```

2. Retrieve a document from collection in mongodb using Find command using condition

>db.Teacher_info.find({sal: 25000})

3. Retrieve a document from collection in mongodb using Find command using or operator

>db.Teacher_info.find({ $or: [{ status: "A" } , { sal:50000 }] })

4. Retrieve a document from collection in mongodb using Find command using greater than , less than, greater than and equal to ,less than and equal to operator

>db. Teacher_info.find({ sal: **{ $gt:** 40000 } })

>db.media.find({ Released : **{$gt :** 2000} }, { **"Cast" : 0** })

{ "_id" : ObjectId("4c4369a3c603000000007ed3"), "Type" : "DVD", "Title" :"Toy Story 3", "Released" : 2010 }

>db.media.find ({ Released : **{$gte** : 1999 } }, { "Cast" : 0 })

{ "_id" : ObjectId("4c43694bc603000000007ed1"), "Type" : "DVD", "Title" :"Matrix, The", "Released" : 1999 }

{ "_id" : ObjectId("4c4369a3c603000000007ed3"), "Type" : "DVD", "Title" :"Toy Story 3", "Released" : 2010 }

>db.media.find ({ Released : **{$lt :** 1999 } }, { "Cast" : 0 })

{ "_id" : ObjectId("4c436969c603000000007ed2"), "Type" : "DVD", "Title" : "Blade Runner", "Released" : 1982 }

>db.media.find({Released : **{$lte:** 1999}}, { "Cast" : 0 })

{ "_id" : ObjectId("4c43694bc603000000007ed1"), "Type" : "DVD", "Title" :"Matrix, The", "Released" : 1999 }

{ "_id" : ObjectId("4c436969c603000000007ed2"), "Type" : "DVD", "Title" :"Blade Runner", "Released" : 1982 }

>db.media.find({Released : **{$gte: 1990, $lt : 2010**}}, { "Cast" : 0 })

{ "_id" : ObjectId("4c43694bc603000000007ed1"), "Type" : "DVD", "Title" :"Matrix, The", "Released" : 1999 }

Retrieval a value from document which contain array field

Exact Match on an Array

db.inventory.find({ tags: ['fruit', 'food', 'citrus'] })

Match an Array Element

db.inventory.find({ tags: 'fruit' })

Match a Specific Element of an Array

db.inventory.find({ 'tags.**0**' : 'fruit' })

6.MongoDB provides a db.collection.findOne() method as a special case of find() that returns a single document.

7.Exclude One Field from a Result Set

>db.records.Find({ "user_id": { $lt: 42} }, { history: 0})

8.Return Two fields and the _id Field

>db.records.find({ "user_id": { $lt: 42} }, { "name": 1, "email": 1})

9.Return Two Fields and Exclude _id

>db.records.find({ "user_id": { $lt: 42} }, { "_id": 0, "name": 1 , "email": 1 })

10. Retrieve a collection in mongodb using Find command and pretty appearance

>db.<collection>.find().pretty()

db.users.find(**collection**

{age:{$gt:18}}, **query criteria**

{name :1,address:1} **projection**

).limit(5)

Retrieve a document in ascending or descending order using 1 for ascending and -1 for descendingfrom collection in mongodb

>db. Teacher_info.find({ status: "A" }).sort({sal: -1 })

>db.audit.find().sort({ $natural: -1 }).limit (10)

>db.Employee.find().sort({_id:-1})

```
{ "_id" : 106, "Name" : "RAJ", "Address" : [ { "City" : "NASIK", "Pin" :
411002 } ], "Department" : [ { "Dept_id" : 113, "Dept_name" : "ACCOUNTING"
} ], "Salary" : 50000 }
{ "_id" : 105, "Name" : "ASHOK", "Address" : [ { "City" : "NASIK", "Pin" :
411002 } ], "Department" : [ { "Dept_id" : 113, "Dept_name" : "ACCOUNTING"
} ], "Salary" : 40000 }
{ "_id" : 104, "Name" : "JOY", "Address" : [ { "City" : "Pune", "Pin" :
444043 } ], "Department" : [ { "Dept_id" : 112, "Dept_name" : "SALES" } ],
"Salary" : 20000 }
{ "_id" : 103, "Name" : "RAM", "Address" : [ { "City" : "Pune", "Pin" :
444043 } ], "Department" : [ { "Dept_id" : 112, "Dept_name" : "SALES" } ],
"Salary" : 10000 }
{ "_id" : 102, "Name" : "AKASH", "Address" : [ { "City" : "Pune", "Pin" :
444043 } ], "Department" : [ { "Dept_id" : 111, "Dept_name" : "HR" } ],
"Salary" : 80000 }
{ "_id" : 101, "Name" : "Dev", "Address" : [ { "City" : "Pune", "Pin" :
444043 } ], "Department" : [ { "Dept_id" : 111, "Dept_name" : "HR" } ],
"Salary" : 78000 }
```

>db.Employee.find().sort({_id:1})

```
{ "_id" : 101, "Name" : "Dev", "Address" : [ { "City" : "Pune", "Pin" :
444043 } ], "Department" : [ { "Dept_id" : 111, "Dept_name" : "HR" } ],
"Salary" : 78000 }
{ "_id" : 102, "Name" : "AKASH", "Address" : [ { "City" : "Pune", "Pin" :
444043 } ], "Department" : [ { "Dept_id" : 111, "Dept_name" : "HR" } ],
"Salary" : 80000 }
```

```
{ "_id" : 103, "Name" : "RAM", "Address" : [ { "City" : "Pune", "Pin" :
444043 } ], "Department" : [ { "Dept_id" : 112, "Dept_name" : "SALES" } ],
"Salary" : 10000 }
{ "_id" : 104, "Name" : "JOY", "Address" : [ { "City" : "Pune", "Pin" :
444043 } ], "Department" : [ { "Dept_id" : 112, "Dept_name" : "SALES" } ],
"Salary" : 20000 }
{ "_id" : 105, "Name" : "ASHOK", "Address" : [ { "City" : "NASIK", "Pin" :
411002 } ], "Department" : [ { "Dept_id" : 113, "Dept_name" : "ACCOUNTING"
} ], "Salary" : 40000 }
{ "_id" : 106, "Name" : "RAJ", "Address" : [ { "City" : "NASIK", "Pin" :
411002 } ], "Department" : [ { "Dept_id" : 113, "Dept_name" : "ACCOUNTING"
} ], "Salary" : 50000 }
>db.Employee.find().sort({$natural:-1}).limit(2)
{ "_id" : 106, "Name" : "RAJ", "Address" : [ { "City" : "NASIK", "Pin" :
411002 } ], "Department" : [ { "Dept_id" : 113, "Dept_name" : "ACCOUNTING"
} ], "Salary" : 50000 }
{ "_id" : 105, "Name" : "ASHOK", "Address" : [ { "City" : "NASIK", "Pin" :
411002 } ], "Department" : [ { "Dept_id" : 113, "Dept_name" : "ACCOUNTING"
} ], "Salary" : 40000 }
```

>db.Employee.find().sort({$natural:1}).limit(2)

```
{ "_id" : 101, "Name" : "Dev", "Address" : [ { "City" : "Pune", "Pin" :
444043 } ], "Department" : [ { "Dept_id" : 111, "Dept_name" : "HR" } ],
"Salary" : 78000 }
{ "_id" : 102, "Name" : "AKASH", "Address" : [ { "City" : "Pune", "Pin" :
444043 } ], "Department" : [ { "Dept_id" : 111, "Dept_name" : "HR" } ],
"Salary" : 80000 }
>db.Employee.find({Salary:{$in:[10000,30000]}})
{ "_id" : 103, "Name" : "RAM", "Address" : [ { "City" : "Pune", "Pin" :
444043 } ], "Department" : [ { "Dept_id" : 112, "Dept_name" : "SALES" } ],
"Salary" : 10000 }
>db.Employee.update({"Name":"RAM"},{ $set :{Address:{City: "Nasik"}}})
WriteResult({ "nMatched" : 1, "nUpserted" : 0, "nModified" : 1 })
>db.Employee.find({"Name":"RAM"})
{ "_id" : 103, "Name" : "RAM", "Address" : { "City" : "Nasik" },
"Department" : [ { "Dept_id" : 112, "Dept_name" : "SALES" } ], "Salary" :
10000 }
>db.Employee.update({"Name":"RAM"},{$inc :{"Salary": 10000 } })
WriteResult({ "nMatched" : 1, "nUpserted" : 0, "nModified" : 1 })
>db.Employee.find({"Name":"RAM"})
{ "_id" : 103, "Name" : "RAM", "Address" : { "City" : "Nasik" },
"Department" : [ { "Dept_id" : 112, "Dept_name" : "SALES" } ], "Salary" :
20000 }
```

Retrieve documentwith a particular from collection in mongodb

>db.Employee.find().limit(2).pretty()

```
{
      "_id" : 101,
```

```
	"Name" : "Dev",
	"Address" : [
		{
			"City" : "Pune",
			"Pin" : 444043
		}
	],
	"Department" : [
		{
			"Dept_id" : 111,
			"Dept_name" : "HR"
		}
	],
	"Salary" : 78000
}
{
	"_id" : 102,
	"Name" : "AKASH",
	"Address" : [
		{
			"City" : "Pune",
			"Pin" : 444043
		}
	],
	"Department" : [
		{
			"Dept_id" : 111,
			"Dept_name" : "HR"
		}
	],
	"Salary" : 80000
}
```

Retrieve document skipping some documents from collection in mongodb

>db.Employee.find().skip(3).pretty()

```
{
	"_id" : 104,
	"Name" : "JOY",
	"Address" : [
		{
			"City" : "Pune",
			"Pin" : 444043
		}
	],
	"Department" : [
		{
			"Dept_id" : 112,
			"Dept_name" : "SALES"
		}
	],
	"Salary" : 20000
```

```
}
{
	"_id" : 105,
	"Name" : "ASHOK",
	"Address" : [
		{
			"City" : "NASIK",
			"Pin" : 411002
		}
	],
	"Department" : [
		{
			"Dept_id" : 113,
			"Dept_name" : "ACCOUNTING"
		}
	],
	"Salary" : 40000
}
{
	"_id" : 106,
	"Name" : "RAJ",
	"Address" : [
		{
			"City" : "NASIK",
			"Pin" : 411002
		}
	],
	"Department" : [
		{
			"Dept_id" : 113,
			"Dept_name" : "ACCOUNTING"
		}
	],
	"Salary" : 50000
}
```

REFERENCE BOOK:

Kristina Chodorow, MongoDB The definitive guide, O'Reilly Publications, ISBN:978-93-5110-269-4,2nd Edition.

CONCLUSION:

Understand to implement data from mongodb database with the help of statement and operators.

Assignment: 2

AIM: Implement Map reduces operation with suitable example on above MongoDB database

- Aggregation framework
- Create and drop different types of indexes and explain () to show the advantage of the indexes.

PROBLEM STATEMENT /DEFINITION

Implement Map reduces operation with suitable example on above MongoDB database

- Aggregation framework
- Create and drop different types of indexes and explain () to show the advantage of the indexes.

OBJECTIVE:

To understand the concept of Mapreduce in mongodb.
To understand the concept of Aggregation in mongodb.

To implement the concept of document oriented databases.

THEORY:

- Implements the MapReduce model for processing large data sets.
- Can choose from one of several output options (inline, new collection, merge, replace, reduce)
- MapReduce functions are written in JavaScript.
- Supports non-sharded and sharded input collections.
- Can be used for incremental aggregation over large collections.
- MongoDB 2.2 implements much better support for sharded map reduce output.
- New feature in the Mongodb2.2.0 production release (August, 2012).
- Designed with specific goals of **improving performance** and **usability.**
- Returns result set inline.

- Supports **non-sharded and sharded**input collections.
- Uses a **"pipeline"** approach where objects are transformed as they pass through a series of pipeline operators such as matching, projecting, sorting, and grouping.
- **Pipeline operators need not produce one output document for every input document:** operators may also generate new documents or filter out documents.
- Map/Reduce involves two steps:
- first, map the data from the collection specified;
- second, reduce the results.

>db.createCollection("Order")

- { "ok" : 1 }

>db.order.insert({cust_id:"A123",amount:500,status:"A"})

- WriteResult({ "nInserted" : 1 })

>db.order.insert({cust_id:"A123",amount:250,status:"A"})

- WriteResult({ "nInserted" : 1 })

>db.order.insert({cust_id:"B212",amount:200,status:"A"})

- WriteResult({ "nInserted" : 1 })

>db.order.insert({cust_id:"A123",amount:300,status:"d"})

- WriteResult({ "nInserted" : 1 })

Map Function

- var mapFunction1 = function()
- { emit(this.cust_id, this.amount);};

Reduce Function

- var reduceFunction1 = function(key, values)
- {return Array.sum(values); };

db.order.mapReduce

(mapFunction1, reduceFunction1, {query: {status: "A" },

```
out:  "order_totals"});
        "result" : "order_totals",
        "timeMillis" : 28,
        "counts" : {
                "input" :3,
                "emit" :3,
                "reduce" : 1,
                "output" : 2
},
"ok" : 1,}
```

>db.order.mapReduce(

Map Function ->   function() { emit(this.cust_id, this.amount);},

Reduce   Function -> function(key, values) { return Array.sum (values)},

Query à   {query: { status:"A"},

Output collection à   out: "order_   totals"})

```
{
        "result" : "order_totals",
        "timeMillis" : 27,
        "counts" : {
                "input" : 3,
                "emit" : 3,
                "reduce" : 1,
                "output" : 2
        },
        "ok" : 1,
}
```

To display result of mapReduce function use collection created in OUT.

Db.<collection name>.find();

db.order_totals.find();

{ "_id" : "A123", "value" : 750 }

{ "_id" : "B212", "value" : 200 }

Implementation of Aggregation:-

```
> use Teacher
switched to db Teacher
>db.Teacher.find()
{ "_id" : 101, "Name" : "Dev", "Address" : [  {  "City" : "Pune",  "Pin" : 444043 } ],
"Department" : [  {  "Dept_id" : 111,  "Dept_name" : "IT" } ], "Salary" : 78000 }
{ "_id" : 135, "Name" : "Jennifer", "Address" : [  {  "City" : "Mumbai",  "Pin" : 444111 } ],
"Department" : [  {  "Dept_id" : 112,  "Dept_name" : "COMP" } ], "Salary" : 65000 }
{ "_id" : 126, "Name" : "Gaurav", "Address" : [  {  "City" : "Nashik",  "Pin" : 444198 } ],
"Department" : [  {  "Dept_id" : 112,  "Dept_name" : "COMP" } ], "Salary" : 90000 }
{ "_id" : 175, "Name" : "Shree", "Address" : [  {  "City" : "Nagpur",  "Pin" : 444158 } ],
"Department" : [  {  "Dept_id" : 113,  "Dept_name" : "ENTC" } ], "Salary" : 42000 }
{ "_id" : 587, "Name" : "Raman", "Address" : [  {  "City" : "Banglore",  "Pin" : 445754 } ],
"Department" : [  {  "Dept_id" : 113,  "Dept_name" : "ENTC" } ], "Salary" : 79000 }
{ "_id" : 674, "Name" : "Mandar", "Address" : [  {  "City" : "Jalgaon",  "Pin" : 465487 } ],
"Department" : [  {  "Dept_id" : 111,  "Dept_name" : "IT" } ], "Salary" : 88000 }
{ "_id" : 573, "Name" : "Manish", "Address" : [  {  "City" : "Washim",  "Pin" : 547353 } ],
"Department" : [  {  "Dept_id" : 112,  "Dept_name" : "COMP" } ], "Salary" : 65000 }

>db.Teacher.aggregate([
... {$group:{_id:"$Department",totalsalary:{$sum:"$Salary"}}}
... ])
{
	"result" : [
		{
			"_id" : [
				{
					"Dept_id" : 113,
					"Dept_name" : "ENTC"
				}
			],
			"totalsalary" : 121000
		},
		{
			"_id" : [
				{
					"Dept_id" : 112,
```

```
                        "Dept_name" : "COMP"
                    }
                ],
                "totalsalary" : 220000
            },
            {
                "_id" : [
                    {
                        "Dept_id" : 111,
                        "Dept_name" : "IT"
                    }
                ],
                "totalsalary" : 166000
            }
        ],
        "ok" : 1
}
```

>db.Teacher.aggregate([{$group:{_id:"$Department",totalsalary:{$sum:"$Salary"}}},{$group:{_id:"$_id.Department",AvgSal:{$sum:"$totalsalary"}}}])

```
{ "result" : [ { "_id" : [ ], "AvgSal" : 507000 } ], "ok" : 1 }
```

>db.Teacher.aggregate([{$group:{_id:"$Department",totalsalary:{$sum:"$Salary"}}},{$match:{totalsalary:{$gte:200000}}}])

```
{
        "result" : [
            {
                "_id" : [
                    {
                        "Dept_id" : 112,
                        "Dept_name" : "COMP"
                    }
                ],
                "totalsalary" : 220000
            }
        ],
        "ok" : 1
}
```

>db.Teacher.aggregate([{$group:{_id:"$Department",totalsalary:{$sum:"$Salary"}}}, { $sort:{totalsalary:1}}])

```
{
        "result" : [
            {
                "_id" : [
                    {
                        "Dept_id" : 113,
```

```
                        "Dept_name" : "ENTC"
                    }
                ],
                "totalsalary" : 121000
            },
            {
                "_id" : [
                    {
                        "Dept_id" : 111,
                        "Dept_name" : "IT"
                    }
                ],
                "totalsalary" : 166000
            },
            {
                "_id" : [
                    {
                        "Dept_id" : 112,
                        "Dept_name" : "COMP"
                    }
                ],
                "totalsalary" : 220000
            }
        ],
        "ok" : 1
}
```

>db.Teacher.aggregate([{$group:{_id:"$Department",totalsalary:{$sum:"$Salary"}}}, { $group: { _id:"$_id.Department", big: { $last: "$_id.Dept_name" }, bigsalary: { $last:"$totalsalary"}, small: { $first:"$_id.Dept_name"}, smallsalary: { $first:"$totalsalary"} }}])

```
{
        "result" : [
            {
                "_id" : [ ],
                "big" : [
                    "IT"
                ],
                "bigsalary" : 166000,
                "small" : [
                    "ENTC"
                ],
                "smallsalary" : 121000
            }
        ],
        "ok" : 1
}
```

REFERENCE BOOK:

Kristina Chodorow, MongoDB The definitive guide, O'Reilly Publications, ISBN:978-93-5110-269-4,2nd Edition.

CONCLUSION:

Understand to mapreduce operation in mongodb

Assignment 3

Aim : Case Study: Design conceptual model using Star and Snowflake schema for any one database

Problem statement: Design conceptual model using Star and Snowflake schema for any one database

OBJECTIVE:

1. To understand concepts of multidimensional data.
2. To understand the the relational implementation of the multidimensional data model is typically a star schema, or a snowflake schema.

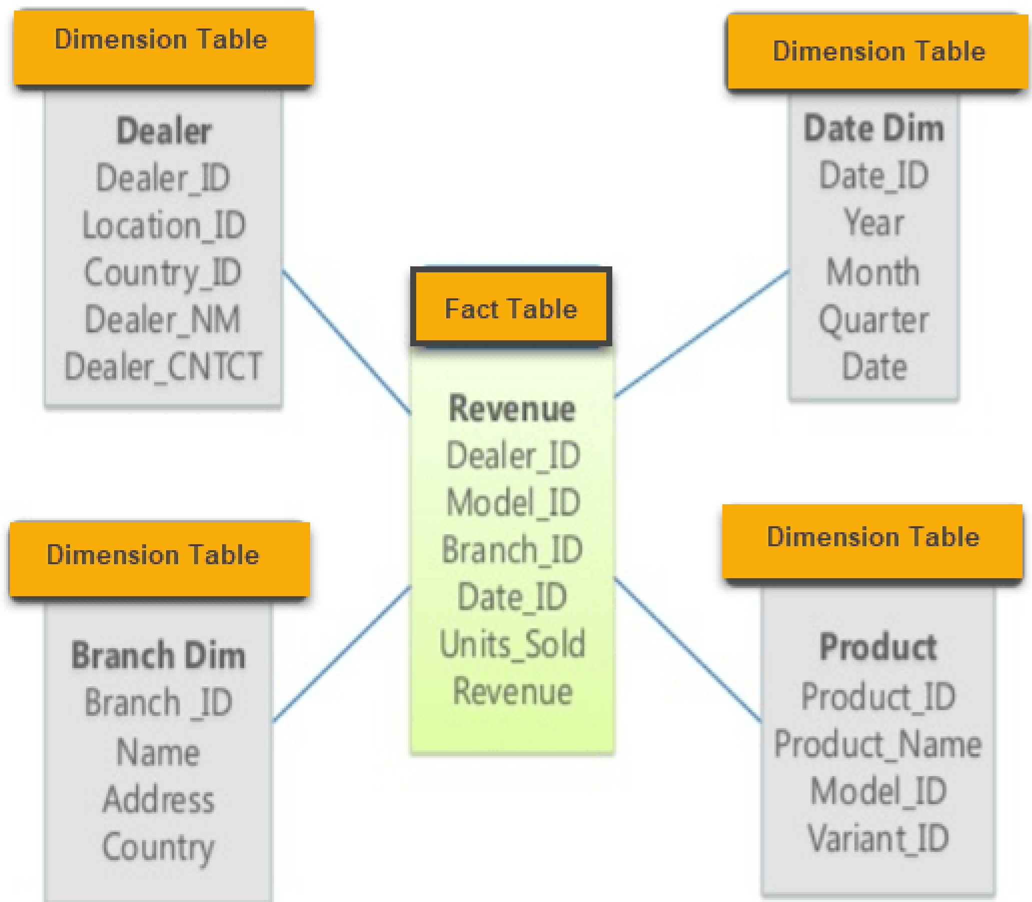
Theory:

The data warehouses are considered modern ancient techniques, since the early days for the relational databases, the idea of the keeping a historical data for reference when it needed has been originated, and the idea was primitive to create archives for the historical data to save these data, despite of the usage of a special techniques for the recovery of these data from the different storage modes. This research applied of structured databases for a trading company operating across the continents, has a set of branches each one has its own stores and showrooms, and the company branch's group of sections with specific activities, such as stores management, showrooms management, accounting management, contracts and other departments. It also assumes that the company center exported software to manage databases for all branches to ensure the safety performance, standardization of processors and prevent the possible errors and bottlenecks problems. Also the research provides this methods the best requirements have been used for the applied of the data warehouse (DW), the information that managed by such an applied must be with high accuracy. It must be emphasized to ensure compatibility information and hedge its security, in schemes domain, been applied to a comparison between the two schemes (Star and Snowflake Schemas) with the concepts of multidimensional database. It turns out that Star Schema is better than Snowflake Schema in (Query complexity, Query performance, Foreign Key Joins),And finally it has been concluded that Star Schema center fact and change, while Snowflake Schema center fact and not change.

Example:

1. *Star Schema*

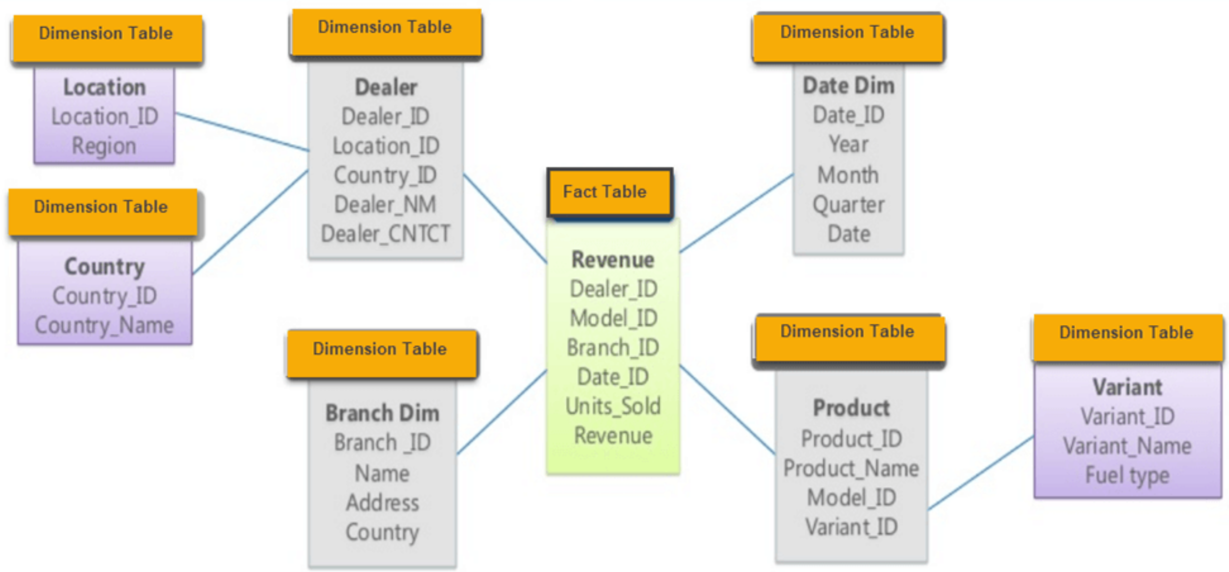
Star Schema in data warehouse, in which the center of the star can have one fact table and a number of associated dimension tables. It is known as star schema as its structure resembles a star. The Star Schema data model is the simplest type of Data Warehouse schema. It is also known as Star Join Schema and is optimized for querying large data sets.



2. **Snowflake Schema?**

Snowflake Schema in data warehouse is a logical arrangement of tables in a multidimensional database such that the ER diagram resembles a snowflake shape. A Snowflake Schema is an extension of a Star Schema, and it adds additional dimensions. The dimension tables are normalized which splits data into additional tables.

In the following Snowflake Schema example, Country is further normalized into an individual table.



- **Conclusion:** Multidimensional schema is especially designed to model data warehouse systems
- The star schema is the simplest type of Data Warehouse schema. It is known as star schema as its structure resembles a star.
- Comparing Snowflake vs Star schema, a Snowflake Schema is an extension of a Star Schema, and it adds additional dimensions. It is called snowflake because its diagram resembles a Snowflake.
- In a star schema, only single join defines the relationship between the fact table and any dimension tables.
- Star schema contains a fact table surrounded by dimension tables.
- Snowflake schema is surrounded by dimension table which are in turn surrounded by dimension table
- A snowflake schema requires many joins to fetch the data.
- Comparing Star vs Snowflake schema, Start schema has simple DB design, while Snowflake schema has very complex DB design.

REFERENCE BOOK:

Jiawei Han, Micheline Kamber, Jian Pei "Data Mining: concepts and techniques", 2nd Edition, Publisher: Elsevier/Morgan Kaufmann.

CONCLUSION:

Understand to concept of multidimensional data.

GROUP D

MINI PROJECT

OR

DATABASE APPLICATION DEVELOPMENT

Assignment: 4

AIM: Design and Implement Database Mini Project**.**

PROBLEM STATEMENT /DEFINITION

Build the mini project based on the requirement document and design prepared as a part of **Database Management Lab** in second year.
Form teams of around 3 to 4 people.
A. Develop the application: Build a suitable GUI by using forms and placing the controls on it for any application. Proper data entry validations are expected.
B. Add the database connection with front end. Implement the basic CRUD operations.
C. Prepare and submit report to include: Title of the Project, Abstract, List the hardware and software requirements at the backend and at the front end, Source Code, Graphical User Interface, Conclusion.

OBJECTIVE:

3. To understand applications of document oriented database by implementing mini project.
4. To learn effective UI designs.
5. To learn to design & implement database system for specific domain.
6. To learn to design system architectural & flow diagram.

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Mini Project Report Format:

Abstract

Acknowledgement

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