Institute of Distance & Open Learning
M.Sc.IT

UNIVERSITY OF MUMBAI

PRACTICAL

MACHINE LEARNING

SUBMITTED BY

PRATIKSHA VINAYAK NIKAM

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SANTACRUZ (EAST), MUMBAI-400 098

CONDUCTED AT

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University of Mumbai

INSTITUTE OF OPEN AND DISTANCE LEARNING

Certificate

This is to certify that Mr./Ms. PRATIKSHA VINAYAK NIKAM, **Seat No**.508864 from Vidyalankar School of Information Technology has successfully completed all the practical of paper **II** titled **MACHINE LEARNING** forM.sc (IT) Part II Semester III prescribed by University of Mumbai, during the academic year **2022 - 2023**.

Signature
Subject-In-Charge

Signature
Head of the Department

College Seal:

Signature
External Examiner

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1.a. Design a simple machine learning model to train the training instances and test the same.

In [2]:
```
from random import randint
TRAIN_SET_LIMIT = 1000
TRAIN_SET_COUNT = 100

TRAIN_INPUT = list()
TRAIN_OUTPUT = list()
for i in range(TRAIN_SET_COUNT):
    a = randint(0, TRAIN_SET_LIMIT)
    b = randint(0, TRAIN_SET_LIMIT)
    c = randint(0, TRAIN_SET_LIMIT)
    op = a + (2*b) + (3*c)
    TRAIN_INPUT.append([a, b, c])
    TRAIN_OUTPUT.append(op)
```

In [3]:
```
from sklearn.linear_model import LinearRegression

predictor = LinearRegression(n_jobs=-1)
predictor.fit(X=TRAIN_INPUT, y=TRAIN_OUTPUT)

```

Out[3]:
```
LinearRegression(n_jobs=-1)
```

In [4]:
```
X_TEST = [[10, 20, 30]]
outcome = predictor.predict(X=X_TEST)
coefficients = predictor.coef_

print('Outcome : {}\nCoefficients : {}'.format(outcome, coefficients))
```

```
Outcome : [140.]
Coefficients : [1. 2. 3.]
```

1.b. Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples. Read the training data from a .CSV file

Source with output

In [8]:
```
#1. Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training
import csv
hypo = ['%','%','%','%','%','%'];

with open('C:/2020-21/IDOL/Sem III/Machine Learning/trainingdata.csv') as csv_file:
    readcsv = csv.reader(csv_file, delimiter=',')
    print(readcsv)

    data = []
    print("\nThe given training examples are:")
    for row in readcsv:
        print(row)
        if row[len(row)-1].upper() == "YES":
            data.append(row)
```

```
<_csv.reader object at 0x000001F8D10B8340>

The given training examples are:
['sky', 'airTemp', 'humidity', 'wind', 'water', 'forecast', 'enjoySport']
['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same', 'Yes']
['Sunny', 'Warm', 'High', 'Strong', 'Warm', 'Same', 'Yes']
['Rainy', 'Cold', 'High', 'Strong', 'Warm', 'Change', 'No']
['Sunny', 'Warm', 'High', 'Strong', 'Cool', 'Change', 'Yes']
```

In [4]:
```
print("\nThe positive examples are:");
for x in data:
    print(x);
print("\n");
```

```
The positive examples are:
['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same', 'Yes']
['Sunny', 'Warm', 'High', 'Strong', 'Warm', 'Same', 'Yes']
['Sunny', 'Warm', 'High', 'Strong', 'Cool', 'Change', 'Yes']
```

In [5]:
```
TotalExamples = len(data);
i=0;
j=0;
k=0;
print("The steps of the Find-s algorithm are :\n",hypo);
list = [];
p=0;
d=len(data[p])-1;
for j in range(d):
    list.append(data[i][j]);
hypo=list;
i=1;
for i in range(TotalExamples):
    for k in range(d):
        if hypo[k]!=data[i][k]:
            hypo[k]='?';
            k=k+1;
        else:
            hypo[k];
    print(hypo);
i=i+1;
```

```
The steps of the Find-s algorithm are :
 ['%', '%', '%', '%', '%', '%']
['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same']
['Sunny', 'Warm', '?', 'Strong', 'Warm', 'Same']
['Sunny', 'Warm', '?', 'Strong', '?', '?']
```

In [6]:
```
print("\nThe maximally specific Find-s hypothesis for the given training examples is :");
list=[];
for i in range(d):
    list.append(hypo[i]);
print(list);
```

```
The maximally specific Find-s hypothesis for the given training examples is :
['Sunny', 'Warm', '?', 'Strong', '?', '?']
```

Data Source TrainingData.csv

sky	airTemp	humidity	wind	water	forecast	enjoySport
Sunny	Warm	Normal	Strong	Warm	Same	Yes
Sunny	Warm	High	Strong	Warm	Same	Yes
Rainy	Cold	High	Strong	Warm	Change	No
Sunny	Warm	High	Strong	Cool	Change	Yes

2. a. Perform Data Loading, Feature selection (Principal Component analysis) and Feature Scoring and Ranking.

- Univariate Selection.

In [8]:
```
# Feature Selection with Univariate Statistical Tests
from pandas import read_csv
from numpy import set_printoptions
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif
# load data
filename = 'C:\\2020-21\\IDOL\\Sem III\\Machine Learning\\pima-indians-diabetes.csv'
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = read_csv(filename, names=names)
array = dataframe.values
X = array[:,0:8]
Y = array[:,8]
# feature extraction
test = SelectKBest(score_func=f_classif, k=4)
fit = test.fit(X, Y)
# summarize scores
set_printoptions(precision=3)
print(fit.scores_)
features = fit.transform(X)
# summarize selected features
print(features[0:5,:])
```

```
[ 39.67  213.162   3.257   4.304  13.281  71.772  23.871  46.141]
[[  6.  148.   33.6  50. ]
 [  1.   85.   26.6  31. ]
 [  8.  183.   23.3  32. ]
 [  1.   89.   28.1  21. ]
 [  0.  137.   43.1  33. ]]
```

- Recursive Feature Elimination.

In [9]:
```
from pandas import read_csv
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
# load data
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = read_csv(url, names=names)
array = dataframe.values
X = array[:,0:8]
Y = array[:,8]
# feature extraction
model = LogisticRegression(solver='lbfgs')
rfe = RFE(model, 3)
fit = rfe.fit(X, Y)
print("Num Features: %d" % fit.n_features_)
print("Selected Features: %s" % fit.support_)import numpy
from pandas import read_csv
from sklearn.decomposition import PCA
# load data
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = read_csv(url, names=names)
array = dataframe.values
X = array[:,0:8]
Y = array[:,8]
# feature extraction
pca = PCA(n_components=3)
fit = pca.fit(X)
# summarize components
print("Explained Variance: %s" % fit.explained_variance_ratio_)
print(fit.components_)
print("Feature Ranking: %s" % fit.ranking_)
```

```
click to scroll output; double click to hide
[ True False False False False  True  True False]
Feature Ranking: [1 2 4 5 6 1 1 3]
```

- Principle Component Analysis.

```
In [10]:
import numpy
from pandas import read_csv
from sklearn.decomposition import PCA
# load data
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = read_csv(url, names=names)
array = dataframe.values
X = array[:,0:8]
Y = array[:,8]
# feature extraction
pca = PCA(n_components=3)
fit = pca.fit(X)
# summarize components
print("Explained Variance: %s" % fit.explained_variance_ratio_)
print(fit.components_)
```

```
Explained Variance: [0.889 0.062 0.026]
[[-2.022e-03  9.781e-02  1.609e-02  6.076e-02  9.931e-01  1.401e-02
   5.372e-04 -3.565e-03]
 [-2.265e-02 -9.722e-01 -1.419e-01  5.786e-02  9.463e-02 -4.697e-02
  -8.168e-04 -1.402e-01]
 [-2.246e-02  1.434e-01 -9.225e-01 -3.070e-01  2.098e-02 -1.324e-01
  -6.400e-04 -1.255e-01]]
```

- Feature Importance.

```
In [11]:
from pandas import read_csv
from sklearn.ensemble import ExtraTreesClassifier
# load data
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = read_csv(url, names=names)
array = dataframe.values
X = array[:,0:8]
Y = array[:,8]
# feature extraction
model = ExtraTreesClassifier(n_estimators=10)
model.fit(X, Y)
print(model.feature_importances_)
```

```
[0.124 0.227 0.094 0.075 0.069 0.148 0.121 0.142]
```

b. For a given set of training data examples stored in a .CSV file, implement and demonstrate the Candidate-Elimination algorithm to output a description of the set of all hypotheses consistent with the training examples

Source and Output

```
In [2]:
#2. For a given set of training data examples stored in a .CSV file,
#implement and demonstrate the Candidate-Elimination algorithm to
#output a description of the set of all hypotheses consistent with the training examples.

import numpy as np
import pandas as pd
```

```
In [3]:
# Loading Data from a CSV File
data = pd.DataFrame(data=pd.read_csv('C:/2020-21/IDOL/Sem III/Machine Learning/trainingdata.csv'))
print(data)
```

	sky	airTemp	humidity	wind	water	forecast	enjoySport
0	Sunny	Warm	Normal	Strong	Warm	Same	Yes
1	Sunny	Warm	High	Strong	Warm	Same	Yes
2	Rainy	Cold	High	Strong	Warm	Change	No
3	Sunny	Warm	High	Strong	Cool	Change	Yes

In [4]:
```
# Separating concept features from Target
concepts = np.array(data.iloc[:,0:-1])
print(concepts)
```

```
[['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
 ['Sunny' 'Warm' 'High' 'Strong' 'Warm' 'Same']
 ['Rainy' 'Cold' 'High' 'Strong' 'Warm' 'Change']
 ['Sunny' 'Warm' 'High' 'Strong' 'Cool' 'Change']]
```

In [5]:
```
# Isolating target into a separate DataFrame
# copying last column to target array
target = np.array(data.iloc[:,-1])
print(target)
```

```
['Yes' 'Yes' 'No' 'Yes']
```

In [6]:
```
def learn(concepts, target):

    '''
    learn() function implements the learning method of the Candidate elimination algorithm.
    Arguments:
        concepts - a data frame with all the features
        target - a data frame with corresponding output values
    '''

    # Initialise S0 with the first instance from concepts
    # .copy() makes sure a new list is created instead of just pointing to the same memory location
    specific_h = concepts[0].copy()
    print("\nInitialization of specific_h and general_h")
    print(specific_h)
    #h=["#" for i in range(0,5)]
    #print(h)

    general_h = [["?" for i in range(len(specific_h))] for i in range(len(specific_h))]
    print(general_h)
    # The learning iterations
    for i, h in enumerate(concepts):

        # Checking if the hypothesis has a positive target
        if target[i] == "Yes":
            for x in range(len(specific_h)):

                # Change values in S & G only if values change
                if h[x] != specific_h[x]:
                    specific_h[x] = '?'
                    general_h[x][x] = '?'

        # Checking if the hypothesis has a positive target
        if target[i] == "No":
            for x in range(len(specific_h)):
                # For negative hyposthesis change values only  in G
                if h[x] != specific_h[x]:
                    general_h[x][x] = specific_h[x]
                else:
                    general_h[x][x] = '?'

        print("\nSteps of Candidate Elimination Algorithm",i+1)
        print(specific_h)
        print(general_h)

    # find indices where we have empty rows, meaning those that are unchanged
    indices = [i for i, val in enumerate(general_h) if val == ['?', '?', '?', '?', '?', '?']]
    for i in indices:
        # remove those rows from general_h
        general_h.remove(['?', '?', '?', '?', '?', '?'])
    # Return final values
    return specific_h, general_h
```

In [7]:
```
s_final, g_final = learn(concepts, target)
print("\nFinal Specific_h:", s_final, sep="\n")
print("\nFinal General_h:", g_final, sep="\n")
```

```
Initialization of specific_h and general_h
['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?',
'?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Steps of Candidate Elimination Algorithm 1
['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?',
'?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Steps of Candidate Elimination Algorithm 2
['Sunny' 'Warm' '?' 'Strong' 'Warm' 'Same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?',
'?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Steps of Candidate Elimination Algorithm 3
['Sunny' 'Warm' '?' 'Strong' 'Warm' 'Same']
[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?'
'?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', 'Same']]

Steps of Candidate Elimination Algorithm 4
['Sunny' 'Warm' '?' 'Strong' '?' '?']
[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?'
'?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Final Specific_h:
['Sunny' 'Warm' '?' 'Strong' '?' '?']

Final General_h:
[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?']]
```

3.a Write a program to implement the naïve Bayesian classifier for a sample training data set stored as a .CSV file. Compute the accuracy of the classifier, considering few test data sets.

Source and Output

In [18]:
```
#Write a program to implement the naïve Bayesian classifier for a sample training
#data set stored as a .CSV file. Compute the accuracy of the classifier, considering
#few test data sets.
# import necessary libarities
import pandas as pd
from sklearn import tree
from sklearn.preprocessing import LabelEncoder
from sklearn.naive_bayes import GaussianNB
```

In [19]:
```
# load data from CSV
data = pd.read_csv('C:/2020-21/IDOL/Sem III/tennisdata.csv')
print("THe first 5 values of data is :\n",data.head())
```

```
THe first 5 values of data is :
     Outlook Temperature Humidity  Windy PlayTennis
0     Sunny         Hot     High  False         No
1     Sunny         Hot     High   True         No
2  Overcast         Hot     High  False        Yes
3     Rainy        Mild     High  False        Yes
4     Rainy        Cool   Normal  False        Yes
```

In [20]:
```
# obtain Train data and Train output
X = data.iloc[:,:-1]
print("\nThe First 5 values of train data is\n",X.head())
```

```
The First 5 values of train data is
     Outlook Temperature Humidity  Windy
0     Sunny         Hot     High  False
1     Sunny         Hot     High   True
2  Overcast         Hot     High  False
3     Rainy        Mild     High  False
4     Rainy        Cool   Normal  False
```

In [21]:
```
y = data.iloc[:,-1]
print("\nThe first 5 values of Train output is\n",y.head())
```

```
The first 5 values of Train output is
 0     No
1     No
2    Yes
3    Yes
4    Yes
Name: PlayTennis, dtype: object
```

In [22]:
```
# Convert then in numbers
le_outlook = LabelEncoder()
X.Outlook = le_outlook.fit_transform(X.Outlook)

le_Temperature = LabelEncoder()
X.Temperature = le_Temperature.fit_transform(X.Temperature)

le_Humidity = LabelEncoder()
X.Humidity = le_Humidity.fit_transform(X.Humidity)

le_Windy = LabelEncoder()
X.Windy = le_Windy.fit_transform(X.Windy)

print("\nNow the Train data is :\n",X.head())
```

```
Now the Train data is :
    Outlook  Temperature  Humidity  Windy
0        2            1         0      0
1        2            1         0      1
2        0            1         0      0
3        1            2         0      0
4        1            0         1      0
```

```
In [23]:
le_PlayTennis = LabelEncoder()
y = le_PlayTennis.fit_transform(y)
print("\nNow the Train output is\n",y)

Now the Train output is
 [0 0 1 1 1 0 1 0 1 1 1 1 1 0]

In [24]:
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.20)

classifier = GaussianNB()
classifier.fit(X_train,y_train)

from sklearn.metrics import accuracy_score
print("Accuracy is:",accuracy_score(classifier.predict(X_test),y_test))

Accuracy is: 1.0
```

Data

Outlook	Temperature	Humidity	Windy	PlayTennis
Sunny	Hot	High	FALSE	No
Sunny	Hot	High	TRUE	No
Overcast	Hot	High	FALSE	Yes
Rainy	Mild	High	FALSE	Yes
Rainy	Cool	Normal	FALSE	Yes
Rainy	Cool	Normal	TRUE	No
Overcast	Cool	Normal	TRUE	Yes
Sunny	Mild	High	FALSE	No
Sunny	Cool	Normal	FALSE	Yes
Rainy	Mild	Normal	FALSE	Yes
Sunny	Mild	Normal	TRUE	Yes
Overcast	Mild	High	TRUE	Yes
Overcast	Hot	Normal	FALSE	Yes
Rainy	Mild	High	TRUE	No

b. Write a program to implement Decision Tree and Random forest with Prediction, Test Score and Confusion Matrix.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
path = 'https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/CognitiveClass/DA0101EN/automobileEDA.csv'
df = pd.read_csv(path)
df.head()
```

Out[2]:

	symboling	normalized-losses	make	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	length	...	compression-ratio	horsepower	peak-rpm	city-mpg	highway-mpg	
0	3	122	alfa-romero	std	two	convertible	rwd	front	88.6	0.811148	...	9.0	111.0	5000.0	21	27	13
1	3	122	alfa-romero	std	two	convertible	rwd	front	88.6	0.811148	...	9.0	111.0	5000.0	21	27	16
2	1	122	alfa-romero	std	two	hatchback	rwd	front	94.5	0.822681	...	9.0	154.0	5000.0	19	26	16
3	2	164	audi	std	four	sedan	fwd	front	99.8	0.848630	...	10.0	102.0	5500.0	24	30	13
4	2	164	audi	std	four	sedan	4wd	front	99.4	0.848630	...	8.0	115.0	5500.0	18	22	17

5 rows × 29 columns

In [3]:
```
df.dtypes
```

Out[3]:
```
symboling              int64
normalized-losses      int64
make                  object
aspiration            object
num-of-doors          object
body-style            object
drive-wheels          object
engine-location       object
wheel-base           float64
length               float64
width                float64
height               float64
curb-weight            int64
engine-type           object
num-of-cylinders      object
engine-size            int64
fuel-system           object
bore                 float64
stroke               float64
compression-ratio    float64
horsepower           float64
peak-rpm             float64
city-mpg               int64
highway-mpg            int64
price                float64
city-L/100km         float64
horsepower-binned     object
diesel                 int64
gas                    int64
dtype: object
```

In [4]:
```
df.describe()
```

Out[4]:

	symboling	normalized-losses	wheel-base	length	width	height	curb-weight	engine-size	bore	stroke	compression-ratio	horsepower
count	201.000000	201.00000	201.000000	201.000000	201.000000	201.000000	201.000000	201.000000	201.000000	197.000000	201.000000	201.000000
mean	0.840796	122.00000	98.797015	0.837102	0.915126	53.766667	2555.666667	126.875622	3.330692	3.256904	10.164279	103.405534
std	1.254802	31.99625	6.066366	0.059213	0.029187	2.447822	517.296727	41.546834	0.268072	0.319256	4.004965	37.365700
min	-2.000000	65.00000	86.600000	0.678039	0.837500	47.800000	1488.000000	61.000000	2.540000	2.070000	7.000000	48.000000
25%	0.000000	101.00000	94.500000	0.801538	0.890278	52.000000	2169.000000	98.000000	3.150000	3.110000	8.600000	70.000000
50%	1.000000	122.00000	97.000000	0.832292	0.909722	54.100000	2414.000000	120.000000	3.310000	3.290000		
75%	2.000000	137.00000	102.400000	0.881788	0.925000	55.500000	2926.000000	141.000000	3.580000	3.410000		
max	3.000000	256.00000	120.900000	1.000000	1.000000	59.800000	4066.000000	326.000000	3.940000	4.170000	2	

In [5]:
```
df.dtypes
for x in df:
    if df[x].dtypes == "int64":
        df[x] = df[x].astype(float)
        print (df[x].dtypes)

```

```
float64
float64
float64
float64
float64
float64
float64
float64
float64
```

In [6]:
```
df = df.select_dtypes(exclude=['object'])
df=df.fillna(df.mean())
X = df.drop('price',axis=1)
y = df['price']
```

In [7]:
```
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)
```

In [8]:
```
from sklearn.ensemble import RandomForestRegressor
regressor = RandomForestRegressor(n_estimators = 1000, random_state = 42)
regressor.fit(X_train, y_train)
```

Out[8]:
```
RandomForestRegressor(n_estimators=1000, random_state=42)
```

In [10]:
```
y_pred = regressor.predict(X_test)
df=pd.DataFrame({'Actual':y_test, 'Predicted':y_pred})
df

```

Out[10]:

	Actual	Predicted
18	6295.0	5828.668000
170	10698.0	10492.447583
107	13860.0	21763.165000
98	13499.0	15317.683000
177	15750.0	16334.467000
...	...	...
30	6855.0	6115.846000
160	8238.0	8129.287000
40	12945.0	11438.811000
56	8845.0	10125.190667
131	15510.0	13600.018833

61 rows × 2 columns

In [11]:
```
from sklearn import metrics
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

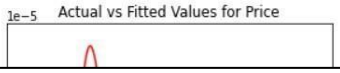
```
Mean Absolute Error: 1993.2901175839186
Mean Squared Error: 9668487.223350348
Root Mean Squared Error: 3109.4191134921566
```

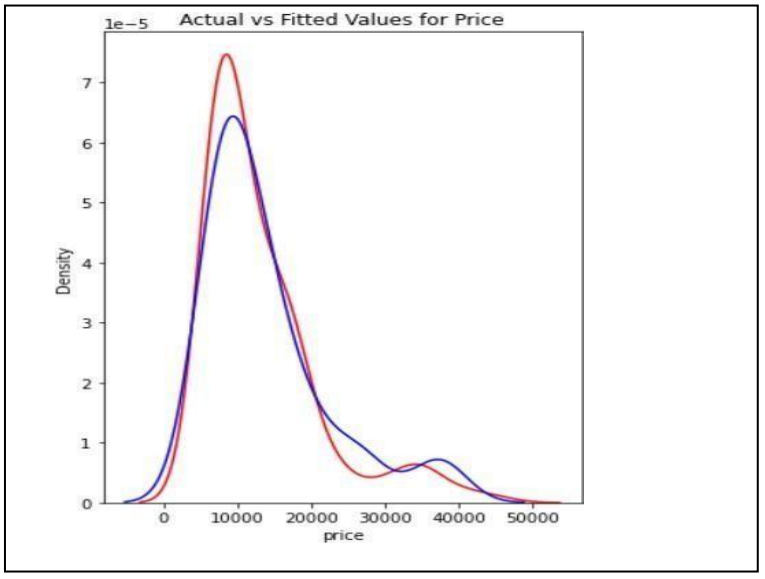
In [12]:
```
# Calculate the absolute errors
errors = abs(y_pred - y_test)
# Print out the mean absolute error (mae)
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')

# Calculate mean absolute percentage error (MAPE)
mape = 100 * (errors / y_test)
# Calculate and display accuracy
accuracy = 100 - np.mean(mape)
print('Accuracy:', round(accuracy, 2), '%.')
```

```
Mean Absolute Error: 1993.29 degrees.
Accuracy: 87.87 %.
```

In [13]:
```
import seaborn as sns
plt.figure(figsize=(5, 7))


ax = sns.distplot(y, hist=False, color="r", label="Actual Value")
sns.distplot(y_pred, hist=False, color="b", label="Fitted Values" , ax=ax)


plt.title('Actual vs Fitted Values for Price')


plt.show()
plt.close()
```

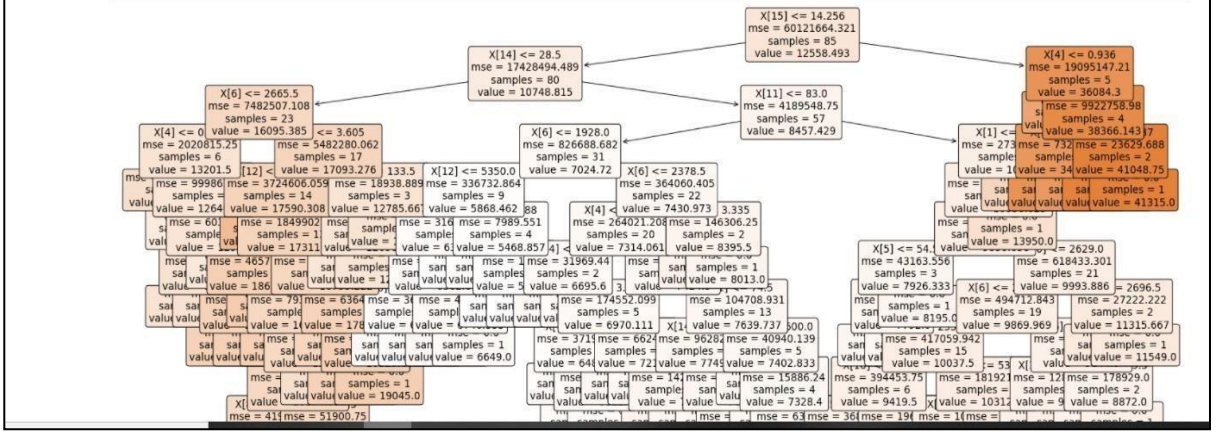
```
C:\Users\hina_\anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprecated functi
d will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with simila
xibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
C:\Users\hina_\anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprecated functi
d will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with simila
xibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```





In [15]:

```
# Import tools needed for visualization
from sklearn.tree import export_graphviz
import pydot
# Pull out one tree from the forest
Tree = regressor.estimators_[5]
# Import tools needed for visualization
from sklearn.tree import export_graphviz
import pydot
# Pull out one tree from the forest
Tree = regressor.estimators_[5]
# Export the image to a dot file
from sklearn import tree
plt.figure(figsize=(25,15))
tree.plot_tree(Tree,filled=True,
               rounded=True,
               fontsize=14);
```

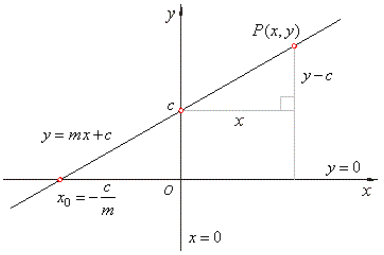


4a. for a given set of training data examples stored in a .CSV file implement Least Square Regression algorithm.

Linear Regression

In statistics, linear regression is a linear approach to modelling the relationship between a dependent variable and one or more independent variables. In the case of one independent variable it is called simple linear regression. For more than one independent variable, the process is called mulitple linear regression. We will be dealing with simple linear regression in this tutorial.
Let **X** be the independent variable and **Y** be the dependent variable. We will define a linear relationship between these two variables as follows:

$$Y = mX + c$$



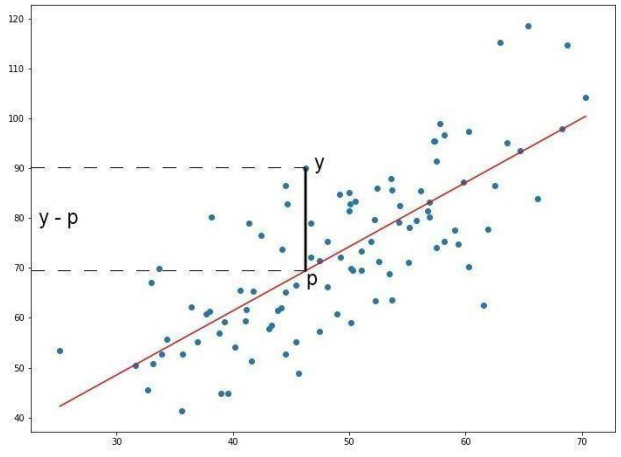
This is the equation for a line that you studied in high school. **m** is the slope of the line and **c** is the y intercept. Today we will use this equation to train our model with a given dataset and predict the value of **Y** for any given value of **X**.

Our challenege today is to determine the value of **m** and **c**, that gives the minimum error for the given dataset. We will be doing this by using the **Least Squares** method.

Finding the Error

So to minimize the error we need a way to calculate the error in the first place. A **loss function** in machine learning is simply a measure of how different the predicted value is from the actual value.
Today we will be using the **Quadratic Loss Function** to calculate the loss or error in our model. It can be defined as:

$$L(x) = \sum_{i=1}^{n} (y_i - p_i)^2$$



We are squaring it because, for the points below the regression line **y - p** will be negative and we don't want negative values in our total error.

Least Squares method

Now that we have determined the loss function, the only thing left to do is minimize it. This is done by finding the partial derivative of **L**, equating it to 0 and then finding an expression for **m** and **c**. After we do the math, we are left with these equations:

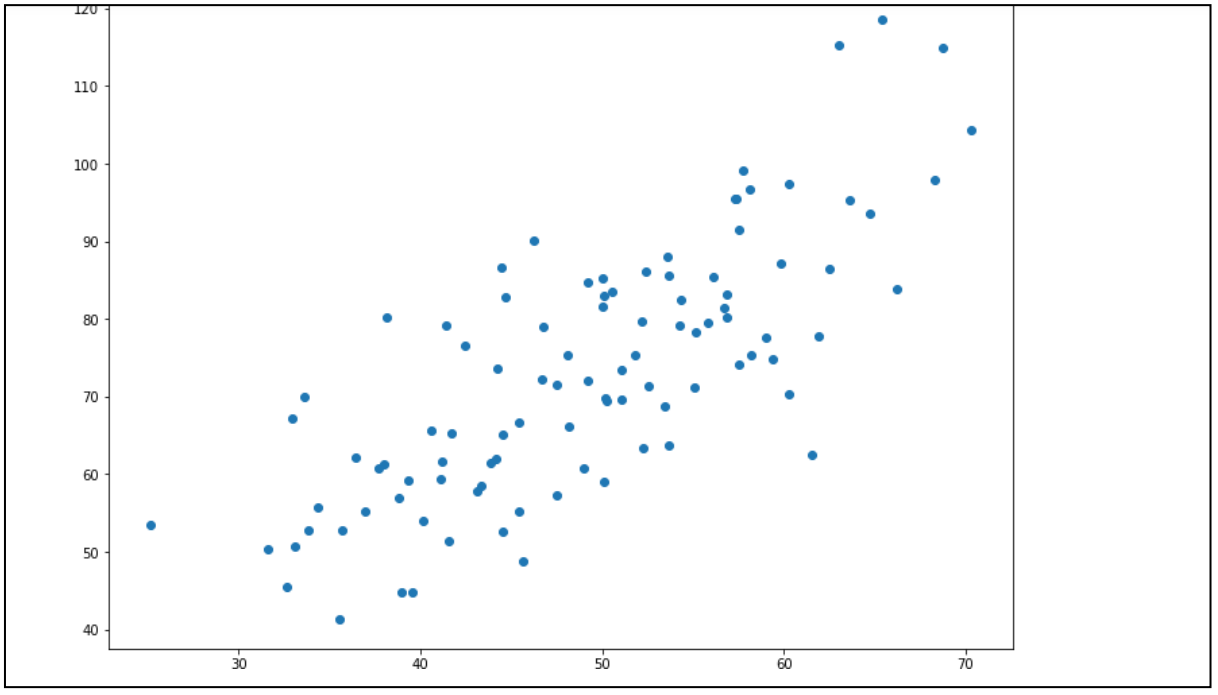
$$m = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

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

Here $\bar{x}$ is the mean of all the values in the input **X** and $\bar{y}$ is the mean of all the values in the desired output **Y**. This is the Least Squares method. Now we will implement this in python and make predictions.

In [4]:
```
# Making imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (12.0, 9.0)
```

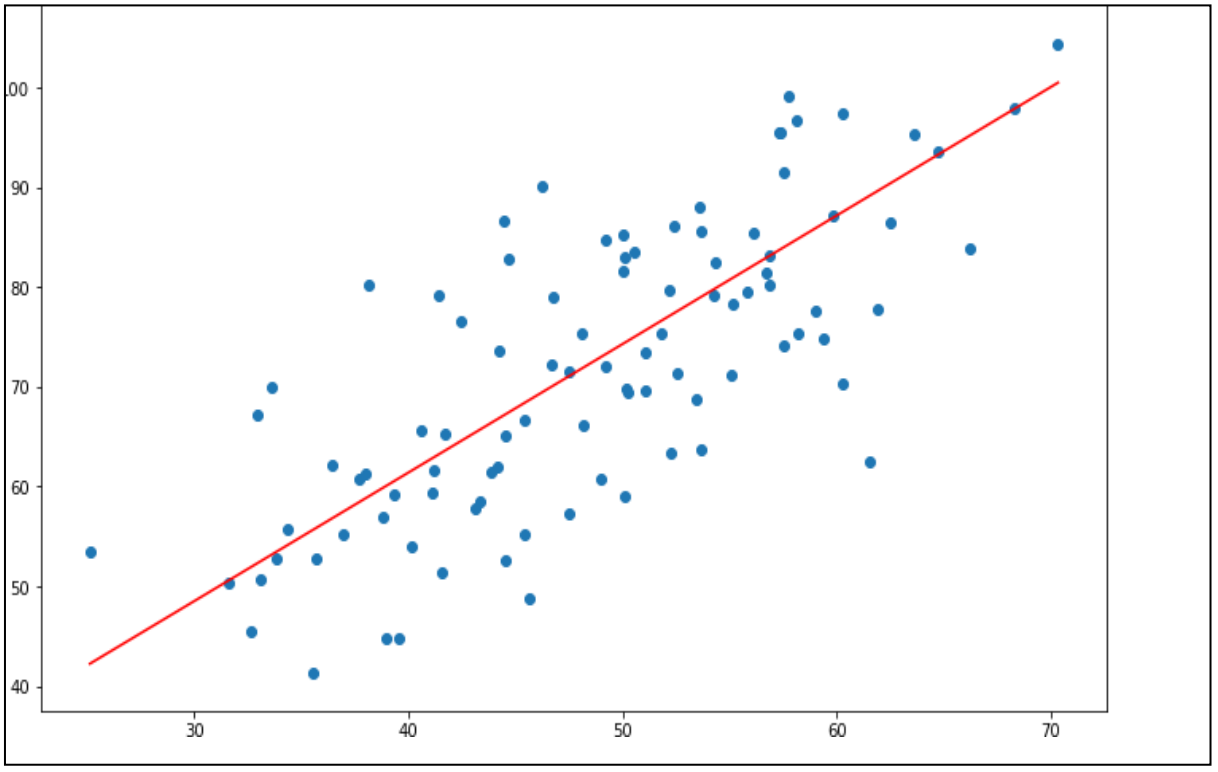
In [5]:
```
# Preprocessing Input data
data = pd.read_csv('C:/Hina/Machine Learning/Data.csv')
X = data.iloc[:, 0]
Y = data.iloc[:, 1]
plt.scatter(X, Y)
plt.show()
```



In [6]:
```
# Building the model
X_mean = np.mean(X)
Y_mean = np.mean(Y)

num = 0
den = 0
for i in range(len(X)):
    num += (X[i] - X_mean)*(Y[i] - Y_mean)
    den += (X[i] - X_mean)**2
m = num / den
c = Y_mean - m*X_mean

print (m, c)
```

```
1.287357370010931 9.908606190326509
```

In [7]:
```
# Making predictions
Y_pred = m*X + c

plt.scatter(X, Y) # actual
plt.plot([min(X), max(X)], [min(Y_pred), max(Y_pred)], color='red') # predicted
plt.show()
```



4 b For a given set of training data examples stored in a .CSV file implement Logistic Regression algorithm

```
In [1]: import numpy as np
        import matplotlib.pyplot as plt
        import pandas as pd
```

```
In [2]: dataset = pd.read_csv('https://raw.githubusercontent.com/mk-gurucharan/Classification/master/DMVWrittenTests.csv')
        X = dataset.iloc[:, [0, 1]].values
        y = dataset.iloc[:, 2].values
        dataset.head(5)
```

Out[2]:

	DMV_Test_1	DMV_Test_2	Results
0	34.623660	78.024693	0
1	30.286711	43.894998	0
2	35.847409	72.902198	0
3	60.182599	86.308552	1
4	79.032736	75.344376	1

```
In [3]: 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 = 0)
```

```
In [4]: from sklearn.preprocessing import StandardScaler
        sc = StandardScaler()
        X_train = sc.fit_transform(X_train)
        X_test = sc.transform(X_test)
```

```
In [5]: from sklearn.linear_model import LogisticRegression
        classifier = LogisticRegression()
        classifier.fit(X_train, y_train)
```

```
Out[5]: LogisticRegression()
```

```
In [6]: y_pred = classifier.predict(X_test)
        y_pred
```

```
Out[6]: array([1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0,
               1, 1, 0], dtype=int64)
```

```
In [7]: from sklearn.metrics import confusion_matrix
        cm = confusion_matrix(y_test, y_pred)
        from sklearn.metrics import accuracy_score
        print ("Accuracy : ", accuracy_score(y_test, y_pred))
        cm
```

```
        Accuracy :  0.88

Out[7]: array([[11,  0],
               [ 3, 11]], dtype=int64)
```

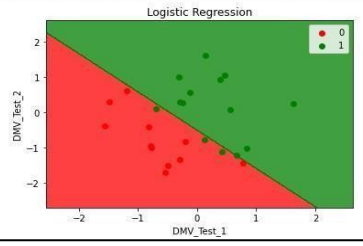
```
In [8]: df = pd.DataFrame({'Real Values':y_test, 'Predicted Values':y_pred})
        df
```

```
Out[8]:
```

	Real Values	Predicted Values
0	1	1
1	0	0
2	0	0
3	0	0
4	1	1
5	1	1
6	1	0
7	1	1
8	0	0
9	1	1
10	0	0
11	0	0
12	0	0
13	1	1
14	1	0
15	1	1
16	0	0
17	1	1
18	1	0
19	1	1
20	0	0
21	0	0
22	1	1
23	1	1
24	0	0

```
In [9]: from matplotlib.colors import ListedColormap
        X_set, y_set = X_test, y_test
        X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1, stop = X_set[:, 0].max() + 1, step = 0.01),
                             np.arange(start = X_set[:, 1].min() - 1, stop = X_set[:, 1].max() + 1, step = 0.01))
        plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(), X2.ravel()]).T).reshape(X1.shape),
                     alpha = 0.75, cmap = ListedColormap(('red', 'green')))
        plt.xlim(X1.min(), X1.max())
        plt.ylim(X2.min(), X2.max())
        for i, j in enumerate(np.unique(y_set)):
            plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
                        c = ListedColormap(('red', 'green'))(i), label = j)
        plt.title('Logistic Regression')
        plt.xlabel('DMV_Test_1')
        plt.ylabel('DMV_Test_2')
        plt.legend()
        plt.show()
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in
case its length matches with *x* & *y*.  Please use the *color* keyword-argument or provide a 2-D array with a single row if yo
u intend to specify the same RGB or RGBA value for all points.
*c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in
case its length matches with *x* & *y*.  Please use the *color* keyword-argument or provide a 2-D array with a single row if yo
u intend to specify the same RGB or RGBA value for all points.
```



5 a. Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample.

In [7]:
```
import pandas as pd
from pandas import DataFrame
df =pd.read_csv('C:\\2020-21\\IDOL\\Sem III\\Machine Learning\\PlayTennis.csv')
df.head(15)
```

Out[7]:

	Unnamed: 0	PlayTennis	Outlook	Temperature	Humidity	Wind
0	0	No	Sunny	Hot	High	Weak
1	1	No	Sunny	Hot	High	Strong
2	2	Yes	Overcast	Hot	High	Weak
3	3	Yes	Rain	Mild	High	Weak
4	4	Yes	Rain	Cool	Normal	Weak
5	5	No	Rain	Cool	Normal	Strong
6	6	Yes	Overcast	Cool	Normal	Strong
7	7	No	Sunny	Mild	High	Weak
8	8	Yes	Sunny	Cool	Normal	Weak
9	9	Yes	Rain	Mild	Normal	Weak
10	10	Yes	Sunny	Mild	Normal	Strong
11	11	Yes	Overcast	Mild	High	Strong
12	12	Yes	Overcast	Hot	Normal	Weak
13	13	No	Rain	Mild	High	Strong

In [9]:
```
#df_tennis.columns[0]
df.keys()[0]
```

Out[9]:
```
'Unnamed: 0'
```

In [11]:
```
#Function to calculate the entropy of probaility of observations
# -p*log2*p

def entropy(probs):
    import math
    return sum( [-prob*math.log(prob, 2) for prob in probs] )

#Function to calulate the entropy of the given Data Sets/List with respect to target attributes
def entropy_of_list(a_list):
    #print("A-list",a_list)
    from collections import Counter
    cnt = Counter(x for x in a_list)   # Counter calculates the propotion of class
   # print("\nClasses:",cnt)
    #print("No and Yes Classes:",a_list.name,cnt)
    num_instances = len(a_list)*1.0   # = 14
    print("\n Number of Instances of the Current Sub Class is {0}:".format(num_instances ))
    probs = [x / num_instances for x in cnt.values()]  # x means no of YES/NO
    print("\n Classes:",min(cnt),max(cnt))
    print(" \n Probabilities of Class {0} is {1}:".format(min(cnt),min(probs)))
    print(" \n Probabilities of Class {0} is {1}:".format(max(cnt),max(probs)))
    return entropy(probs) # Call Entropy :

# The initial entropy of the YES/NO attribute for our dataset.
print("\n  INPUT DATA SET FOR ENTROPY CALCULATION:\n", df['PlayTennis'])

total_entropy = entropy_of_list(df['PlayTennis'])

print("\n Total Entropy of PlayTennis Data Set:",total_entropy)
```

```
 INPUT DATA SET FOR ENTROPY CALCULATION:
 0      No
1       No
2      Yes
3      Yes
4      Yes
5       No
6      Yes
7       No
8      Yes
9      Yes
10     Yes
11     Yes
12     Yes
13      No
Name: PlayTennis, dtype: object

 Number of Instances of the Current Sub Class is 14.0:

 Classes: No Yes

 Probabilities of Class No is 0.35714285714285715:

 Probabilities of Class Yes is 0.6428571428571429:

 Total Entropy of PlayTennis Data Set: 0.9402859586706309
```

In [15]:

```python
def information_gain(df, split_attribute_name, target_attribute_name, trace=0):
    print("Information Gain Calculation of ",split_attribute_name)
    '''
    Takes a DataFrame of attributes, and quantifies the entropy of a target
    attribute after performing a split along the values of another attribute.
    '''
    # Split Data by Possible Vals of Attribute:
    df_split = df.groupby(split_attribute_name)
   # for name,group in df_split:
    #    print("Name:\n",name)
     #   print("Group:\n",group)

    # Calculate Entropy for Target Attribute, as well as
    # Proportion of Obs in Each Data-Split
    nobs = len(df.index) * 1.0
   # print("NOBS",nobs)
    df_agg_ent = df_split.agg({target_attribute_name : [entropy_of_list, lambda x: len(x)/nobs] })[target_attribute_name]
    #print([target_attribute_name])
    #print(" Entropy List ",entropy_of_list)
    #print("DFAGGENT",df_agg_ent)
    df_agg_ent.columns = ['Entropy', 'PropObservations']
    #if trace: # helps understand what fxn is doing:
     #   print(df_agg_ent)

    # Calculate Information Gain:
    new_entropy = sum( df_agg_ent['Entropy'] * df_agg_ent['PropObservations'] )
    old_entropy = entropy_of_list(df[target_attribute_name])
    return old_entropy - new_entropy


print('Info-gain for Outlook is :'+str( information_gain(df, 'Outlook', 'PlayTennis')),"\n")
print('\n Info-gain for Humidity is: ' + str( information_gain(df, 'Humidity', 'PlayTennis')),"\n")
print('\n Info-gain for Wind is:' + str( information_gain(df, 'Wind', 'PlayTennis')),"\n")
print('\n Info-gain for Temperature is:' + str( information_gain(df, 'Temperature','PlayTennis')),"\n")
```

```
Information Gain Calculation of  Outlook

 Number of Instances of the Current Sub Class is 4.0:

 Classes: Yes Yes

 Probabilities of Class Yes is 1.0:

 Probabilities of Class Yes is 1.0:

 Number of Instances of the Current Sub Class is 5.0:

 Classes: No Yes

 Probabilities of Class No is 0.4:

 Probabilities of Class Yes is 0.6:

 Number of Instances of the Current Sub Class is 5.0:
```

In [16]:

```
def id3(df, target_attribute_name, attribute_names, default_class=None):

    ## Tally target attribute:
    from collections import Counter
    cnt = Counter(x for x in df[target_attribute_name])# class of YES /NO

    ## First check: Is this split of the dataset homogeneous?
    if len(cnt) == 1:
        return next(iter(cnt))  # next input data set, or raises StopIteration when EOF is hit.

    ## Second check: Is this split of the dataset empty?
    # if yes, return a default value
    elif df.empty or (not attribute_names):
        return default_class  # Return None for Empty Data Set

    ## Otherwise: This dataset is ready to be devied up!
    else:
        # Get Default Value for next recursive call of this function:
        default_class = max(cnt.keys()) #No of YES and NO Class
        # Compute the Information Gain of the attributes:
        gainz = [information_gain(df, attr, target_attribute_name) for attr in attribute_names] #
        index_of_max = gainz.index(max(gainz)) # Index of Best Attribute
        # Choose Best Attribute to split on:
        best_attr = attribute_names[index_of_max]

        # Create an empty tree, to be populated in a moment
        tree = {best_attr:{}} # Initiate the tree with best attribute as a node
        remaining_attribute_names = [i for i in attribute_names if i != best_attr]

        # Split dataset
        # On each split, recursively call this algorithm.
        # populate the empty tree with subtrees, which
        # are the result of the recursive call
        for attr_val, data_subset in df.groupby(best_attr):
            subtree = id3(data_subset,
                          target_attribute_name,
                          remaining_attribute_names,
                          default_class)
            tree[best_attr][attr_val] = subtree
        return tree
```

In [17]:

```
# Get Predictor Names (all but 'class')
attribute_names = list(df.columns)
print("List of Attributes:", attribute_names)
attribute_names.remove('PlayTennis') #Remove the class attribute
print("Predicting Attributes:", attribute_names)
```

```
List of Attributes: ['Unnamed: 0', 'PlayTennis', 'Outlook', 'Temperature', 'Humidity', 'Wind']
Predicting Attributes: ['Unnamed: 0', 'Outlook', 'Temperature', 'Humidity', 'Wind']
```

In [18]:

```
# Run Algorithm:
from pprint import pprint
tree = id3(df,'PlayTennis',attribute_names)
print("\n\nThe Resultant Decision Tree is :\n")
#print(tree)
pprint(tree)
attribute = next(iter(tree))
print("Best Attribute :\n",attribute)
print("Tree Keys:\n",tree[attribute].keys())
```

```
Information Gain Calculation of  Unnamed: 0

 Number of Instances of the Current Sub Class is 1.0:

 Classes: No No

 Probabilities of Class No is 1.0:

 Probabilities of Class No is 1.0:

 Number of Instances of the Current Sub Class is 1.0:

 Classes: No No

 Probabilities of Class No is 1.0:

 Probabilities of Class No is 1.0:

 Number of Instances of the Current Sub Class is 1.0:
```

```
Number of Instances of the Current Sub Class is 1.0:

Classes: Yes Yes

Probabilities of Class Yes is 1.0:

Probabilities of Class Yes is 1.0:

Number of Instances of the Current Sub Class is 1.0:

Classes: Yes Yes

Probabilities of Class Yes is 1.0:

Probabilities of Class Yes is 1.0:

Number of Instances of the Current Sub Class is 1.0:

Classes: Yes Yes
```

```
Classes: Yes Yes

Probabilities of Class Yes is 1.0:

Probabilities of Class Yes is 1.0:

Number of Instances of the Current Sub Class is 1.0:

Classes: No No

Probabilities of Class No is 1.0:

Probabilities of Class No is 1.0:

Number of Instances of the Current Sub Class is 1.0:

Classes: Yes Yes
```

```
Probabilities of Class No is 1.0:

Probabilities of Class No is 1.0:

Number of Instances of the Current Sub Class is 1.0:

Classes: Yes Yes

Probabilities of Class Yes is 1.0:

Probabilities of Class Yes is 1.0:

Number of Instances of the Current Sub Class is 1.0:

Classes: No No

Probabilities of Class No is 1.0:
```

```
Probabilities of Class No is 1.0:

Number of Instances of the Current Sub Class is 1.0:

Classes: Yes Yes

Probabilities of Class Yes is 1.0:

Probabilities of Class Yes is 1.0:

Number of Instances of the Current Sub Class is 1.0:

Classes: Yes Yes

Probabilities of Class Yes is 1.0:

Probabilities of Class Yes is 1.0:
```

```
Number of Instances of the Current Sub Class is 1.0:

Classes: Yes Yes

Probabilities of Class Yes is 1.0:

Probabilities of Class Yes is 1.0:

Number of Instances of the Current Sub Class is 1.0:

Classes: Yes Yes

Probabilities of Class Yes is 1.0:

Probabilities of Class Yes is 1.0:

Number of Instances of the Current Sub Class is 1.0:
```

```
Classes: Yes Yes

Probabilities of Class Yes is 1.0:

Probabilities of Class Yes is 1.0:

Number of Instances of the Current Sub Class is 1.0:

Classes: No No

Probabilities of Class No is 1.0:

Probabilities of Class No is 1.0:

Number of Instances of the Current Sub Class is 14.0:

Classes: No Yes
```

```
 Probabilities of Class No is 0.35714285714285715:

 Probabilities of Class Yes is 0.6428571428571429:
Information Gain Calculation of  Outlook

 Number of Instances of the Current Sub Class is 4.0:

 Classes: Yes Yes

 Probabilities of Class Yes is 1.0:

 Probabilities of Class Yes is 1.0:

 Number of Instances of the Current Sub Class is 5.0:

 Classes: No Yes
```

```
    Probabilities of Class No is 0.4:

    Probabilities of Class Yes is 0.6:

    Number of Instances of the Current Sub Class is 5.0:

    Classes: No Yes

    Probabilities of Class No is 0.4:

    Probabilities of Class Yes is 0.6:

    Number of Instances of the Current Sub Class is 14.0:

    Classes: No Yes

    Probabilities of Class No is 0.35714285714285715:
```

```
     Probabilities of Class Yes is 0.6428571428571429:
    Information Gain Calculation of  Temperature

     Number of Instances of the Current Sub Class is 4.0:

     Classes: No Yes

     Probabilities of Class No is 0.25:

     Probabilities of Class Yes is 0.75:

     Number of Instances of the Current Sub Class is 4.0:

     Classes: No Yes

     Probabilities of Class No is 0.5:
```

```
Probabilities of Class Yes is 0.5:

Number of Instances of the Current Sub Class is 6.0:

Classes: No Yes

Probabilities of Class No is 0.3333333333333333:

Probabilities of Class Yes is 0.6666666666666666:

Number of Instances of the Current Sub Class is 14.0:

Classes: No Yes

Probabilities of Class No is 0.35714285714285715:

Probabilities of Class Yes is 0.6428571428571429:
Information Gain Calculation of  Humidity
```

```
Number of Instances of the Current Sub Class is 7.0:

Classes: No Yes

Probabilities of Class No is 0.42857142857142855:

Probabilities of Class Yes is 0.5714285714285714:

Number of Instances of the Current Sub Class is 7.0:

Classes: No Yes

Probabilities of Class No is 0.14285714285714285:

Probabilities of Class Yes is 0.8571428571428571:

Number of Instances of the Current Sub Class is 14.0:
```

```
Number of Instances of the Current Sub Class is 14.0:

Classes: No Yes

Probabilities of Class No is 0.35714285714285715:

Probabilities of Class Yes is 0.6428571428571429:
Information Gain Calculation of  Wind

Number of Instances of the Current Sub Class is 6.0:

Classes: No Yes

Probabilities of Class No is 0.5:

Probabilities of Class Yes is 0.5:

Number of Instances of the Current Sub Class is 8.0:
```

```
Classes: No Yes

Probabilities of Class No is 0.25:

Probabilities of Class Yes is 0.75:

Number of Instances of the Current Sub Class is 14.0:

Classes: No Yes

Probabilities of Class No is 0.35714285714285715:

Probabilities of Class Yes is 0.6428571428571429:
```

```
The Resultant Decision Tree is :

{'Unnamed: 0': {0: 'No',
                1: 'No',
                2: 'Yes',
                3: 'Yes',
                4: 'Yes',
                5: 'No',
                6: 'Yes',
                7: 'No',
                8: 'Yes',
                9: 'Yes',
                10: 'Yes',
                11: 'Yes',
                12: 'Yes',
                13: 'No'}}
```

```
                13: 'No'}}
Best Attribute :
 Unnamed: 0
Tree Keys:
 dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
```

In [19]:

```
def classify(instance, tree, default=None): # Instance of Play Tennis with Predicted

    #print("Instance:",instance)
    attribute = next(iter(tree)) # Outlook/Humidity/Wind
    print("Key:",tree.keys())  # [Outlook,Humidity,Wind ]
    print("Attribute:",attribute) # [Key /Attribute Both are same ]

    # print("Insance of Attribute :",instance[attribute],attribute)
    if instance[attribute] in tree[attribute].keys(): # Value of the attributs in  set of Tree keys
        result = tree[attribute][instance[attribute]]
        print("Instance Attribute:",instance[attribute],"TreeKeys :",tree[attribute].keys())
        if isinstance(result, dict): # this is a tree, delve deeper
            return classify(instance, result)
        else:
            return result # this is a label
    else:
        return default
```

In [21]:

```
df['predicted'] = df.apply(classify, axis=1, args=(tree,'No') )
    # classify func allows for a default arg: when tree doesn't have answer for a particular
    # combitation of attribute-values, we can use 'no' as the default guess

print(df['predicted'])

print('\n Accuracy is:\n' + str( sum(df['PlayTennis']==df['predicted'] ) / (1.0*len(df.index)) ))


df[['PlayTennis', 'predicted']]
```

```
Key: dict_keys(['Unnamed: 0'])
Attribute: Unnamed: 0
Instance Attribute: 1 TreeKeys : dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
Key: dict_keys(['Unnamed: 0'])
Attribute: Unnamed: 0
Instance Attribute: 2 TreeKeys : dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
Key: dict_keys(['Unnamed: 0'])
Attribute: Unnamed: 0
Instance Attribute: 3 TreeKeys : dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
Key: dict_keys(['Unnamed: 0'])
Attribute: Unnamed: 0
Instance Attribute: 4 TreeKeys : dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
Key: dict_keys(['Unnamed: 0'])
Attribute: Unnamed: 0
Instance Attribute: 5 TreeKeys : dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
Key: dict_keys(['Unnamed: 0'])
Attribute: Unnamed: 0
Instance Attribute: 6 TreeKeys : dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
Key: dict_keys(['Unnamed: 0'])
Attribute: Unnamed: 0
Instance Attribute: 7 TreeKeys : dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
Key: dict_keys(['Unnamed: 0'])
Attribute: Unnamed: 0
Instance Attribute: 8 TreeKeys : dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
Key: dict_keys(['Unnamed: 0'])
Attribute: Unnamed: 0
Instance Attribute: 9 TreeKeys : dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
Key: dict_keys(['Unnamed: 0'])
Attribute: Unnamed: 0
Instance Attribute: 10 TreeKeys : dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
Key: dict_keys(['Unnamed: 0'])
Attribute: Unnamed: 0
Instance Attribute: 11 TreeKeys : dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
Key: dict_keys(['Unnamed: 0'])
Attribute: Unnamed: 0
Instance Attribute: 12 TreeKeys : dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
```

```
Instance Attribute: 13 TreeKeys : dict_keys([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])
0      No
1      No
2     Yes
3     Yes
4     Yes
5      No
6     Yes
7      No
8     Yes
9     Yes
10    Yes
11    Yes
12    Yes
13     No
Name: predicted, dtype: object

 Accuracy is:
1.0
```

Out[21]:

Out[21]:

	PlayTennis	predicted
0	No	No
1	No	No
2	Yes	Yes
3	Yes	Yes
4	Yes	Yes
5	No	No
6	Yes	Yes
7	No	No
8	Yes	Yes
9	Yes	Yes
10	Yes	Yes
11	Yes	Yes
12	Yes	Yes
13	No	No

In [22]:

```
training_data = df.iloc[1:-4] # all but last four instances
test_data  = df.iloc[-4:] # just the last four
train_tree = id3(training_data, 'PlayTennis', attribute_names)

test_data['predicted2'] = test_data.apply(                              # <---- test_data source
                                          classify,
                                          axis=1,
                                          args=(train_tree,'Yes') ) # <---- train_data tree


print ('\n\n Accuracy is : ' + str( sum(test_data['PlayTennis']==test_data['predicted2'] ) / (1.0*len(test_data.index)) ))
```

```
Information Gain Calculation of  Unnamed: 0

 Number of Instances of the Current Sub Class is 1.0:

 Classes: No No

 Probabilities of Class No is 1.0:

 Probabilities of Class No is 1.0:

 Number of Instances of the Current Sub Class is 1.0:

 Classes: Yes Yes

 Probabilities of Class Yes is 1.0:

 Probabilities of Class Yes is 1.0:

 Number of Instances of the Current Sub Class is 1.0:
```

```
Probabilities of Class Yes is 1.0:

Probabilities of Class Yes is 1.0:

Number of Instances of the Current Sub Class is 1.0:

Classes: Yes Yes

Probabilities of Class Yes is 1.0:

Probabilities of Class Yes is 1.0:

Number of Instances of the Current Sub Class is 1.0:

Classes: No No

Probabilities of Class No is 1.0:
```

```
Probabilities of Class No is 1.0:
Number of Instances of the Current Sub Class is 1.0:
Classes: Yes Yes
Probabilities of Class Yes is 1.0:
Probabilities of Class Yes is 1.0:
Number of Instances of the Current Sub Class is 1.0:
Classes: No No
Probabilities of Class No is 1.0:
Probabilities of Class No is 1.0:
```

```
Number of Instances of the Current Sub Class is 1.0:

Classes: Yes Yes

Probabilities of Class Yes is 1.0:

Probabilities of Class Yes is 1.0:

Number of Instances of the Current Sub Class is 1.0:

Classes: Yes Yes

Probabilities of Class Yes is 1.0:

Probabilities of Class Yes is 1.0:

Number of Instances of the Current Sub Class is 9.0:
```

```
Classes: No Yes
Probabilities of Class No is 0.3333333333333333:
Probabilities of Class Yes is 0.6666666666666666:
Information Gain Calculation of  Outlook
Number of Instances of the Current Sub Class is 2.0:
Classes: Yes Yes
Probabilities of Class Yes is 1.0:
Probabilities of Class Yes is 1.0:
Number of Instances of the Current Sub Class is 4.0:
Classes: No Yes
```

```
Classes: No Yes

Probabilities of Class No is 0.25:

Probabilities of Class Yes is 0.75:

Number of Instances of the Current Sub Class is 3.0:

Classes: No Yes

Probabilities of Class No is 0.3333333333333333:

Probabilities of Class Yes is 0.6666666666666666:

Number of Instances of the Current Sub Class is 9.0:

Classes: No Yes
```

```
Probabilities of Class No is 0.3333333333333333:

Probabilities of Class Yes is 0.6666666666666666:
Information Gain Calculation of  Temperature

Number of Instances of the Current Sub Class is 4.0:

Classes: No Yes

Probabilities of Class No is 0.25:

Probabilities of Class Yes is 0.75:

Number of Instances of the Current Sub Class is 2.0:

Classes: No Yes

Probabilities of Class No is 0.5:
```

```
Probabilities of Class No is 0.5:

Probabilities of Class Yes is 0.5:

Number of Instances of the Current Sub Class is 3.0:

Classes: No Yes

Probabilities of Class No is 0.3333333333333333:

Probabilities of Class Yes is 0.6666666666666666:

Number of Instances of the Current Sub Class is 9.0:

Classes: No Yes

Probabilities of Class No is 0.3333333333333333:

Probabilities of Class Yes is 0.6666666666666666:
```

```
 Probabilities of Class Yes is 0.6666666666666666:
Information Gain Calculation of  Humidity

 Number of Instances of the Current Sub Class is 4.0:

 Classes: No Yes

 Probabilities of Class No is 0.5:

 Probabilities of Class Yes is 0.5:

 Number of Instances of the Current Sub Class is 5.0:

 Classes: No Yes

 Probabilities of Class No is 0.2:

 Probabilities of Class Yes is 0.8:
```

5 b Write a program to implement k-Nearest Neighbor algorithm to classify the iris data set

```
In [1]: import pandas as pd
        import numpy as np
        import math
        import operator
```

```
In [3]: col=['sepal_length','sepal_width','petal_length','petal_width','type']
        iris=pd.read_csv("C:\Hina\Machine Learning\iris.xlsx",names=col)
```

```
In [4]: print("First five rows")
        print(iris.head())
        print("*********")
        print("columns",iris.columns)
        print("*********")
        print("shape:",iris.shape)
        print("*********")
        print("Size:",iris.size)
        print("*********")
        print("no of samples available for each type")
        print(iris['type'].value_counts())
        print("*********")
        print(iris.describe())
```

```
First five rows
   sepal_length  sepal_width  petal_length  petal_width         type
0           5.1          3.5           1.4          0.2  Iris-setosa
1           4.9          3.0           1.4          0.2  Iris-setosa
2           4.7          3.2           1.3          0.2  Iris-setosa
3           4.6          3.1           1.5          0.2  Iris-setosa
4           5.0          3.6           1.4          0.2  Iris-setosa
*********
columns Index(['sepal_length', 'sepal_width', 'petal_length', 'petal_width', 'type'], dtype='object')
*********
shape: (150, 5)
*********
Size: 750
*********
no of samples available for each type
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: type, dtype: int64
*********
       sepal_length  sepal_width  petal_length  petal_width
count    150.000000   150.000000    150.000000   150.000000
mean       5.843333     3.054000      3.758667     1.198667
std        0.828066     0.433594      1.764420     0.763161
min        4.300000     2.000000      1.000000     0.100000
25%        5.100000     2.800000
50%        5.800000     3.000000
75%        6.400000     3.300000
```



```
In [6]: def euclidianDistance(data1, data2, length):
            distance = 0
            for x in range(length):
                distance += np.square(data1[x] - data2[x])

            return np.sqrt(distance)
        def knn(trainingSet, testInstance, k):

            distances = {}
            sort = {}
            length = testInstance.shape[1]
            print(length)


            # Calculating euclidean distance between each row of training data and test data
            for x in range(len(trainingSet)):


                dist = euclidianDistance(testInstance, trainingSet.iloc[x], length)
                distances[x] = dist[0]
```

```
# Sorting them on the basis of distance
sorted_d = sorted(distances.items(), key=operator.itemgetter(1)) #by using it we store indices also
sorted_d1 = sorted(distances.items())
print(sorted_d[:5])
print(sorted_d1[:5])


neighbors = []


# Extracting top k neighbors
for x in range(k):
    neighbors.append(sorted_d[x][0])
    counts = {"Iris-setosa":0,"Iris-versicolor":0,"Iris-virginica":0}


# Calculating the most freq class in the neighbors
for x in range(len(neighbors)):
    response = trainingSet.iloc[neighbors[x]][-1]

    if response in counts:
        counts[response] += 1
    else:
        counts[response] = 1
```

```
    print(counts)
    sortedVotes = sorted(counts.items(), key=operator.itemgetter(1), reverse=True)
    print(sortedVotes)
    return(sortedVotes[0][0], neighbors)
```

In [8]:
```
testSet = [[1.4, 3.6, 3.4, 1.2]]
test = pd.DataFrame(testSet)
result,neigh = knn(iris, test, 4)#here we gave k=4
print("And the flower is:",result)
print("the neighbors are:",neigh)
```

```
4
[(57, 3.706750598570128), (8, 3.8065732621348567), (42, 3.817066936798463), (93, 3.8340579025361627), (38, 3.8431757701151272)]
[(0, 4.32434966208793), (1, 4.196427051671457), (2, 4.057092555020159), (3, 3.8858718455450894), (4, 4.237924020083418)]
{'Iris-setosa': 2, 'Iris-versicolor': 2, 'Iris-virginica': 0}
[('Iris-setosa', 2), ('Iris-versicolor', 2), ('Iris-virginica', 0)]
And the flower is: Iris-setosa
the neighbors are: [57, 8, 42, 93]
```

In [11]:
```
from sklearn.neighbors import KNeighborsClassifier
x=iris.iloc[:,:4] #all parameters
y=iris["type"] #class labels
```

In [12]:
```
neigh=KNeighborsClassifier(n_neighbors=4)
neigh.fit(iris.iloc[:,:4],iris["type"])
```

Out[12]:
```
KNeighborsClassifier(n_neighbors=4)
```

In [13]:
```
testSet = [[1.4, 3.6, 3.4, 1.2]]
test = pd.DataFrame(testSet)
print(test)
print("predicted:",neigh.predict(test))
print("neighbors",neigh.kneighbors(test))
```

```
     0    1    2    3
0  1.4  3.6  3.4  1.2
predicted: ['Iris-setosa']
neighbors (array([[3.7067506 , 3.80657326, 3.81706694, 3.8340579 ]]), array([[57,  8, 42, 93]], dtype=int64))
```

In [15]:
```
import pandas as pd
import numpy as np
import math
import operator
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import recall_score , precision_score , roc_auc_score ,roc_curve
from sklearn.metrics import confusion_matrix
from sklearn.svm import SVC
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore") #to remove unwanted warnings
```

In [16]:
```
x=iris.iloc[1:,:3]#features
y=iris.iloc[1:,4:]#class labels
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2)
#test_size determines the percentage of test data you want here
#train=80% and test=20% data is randomly split
```

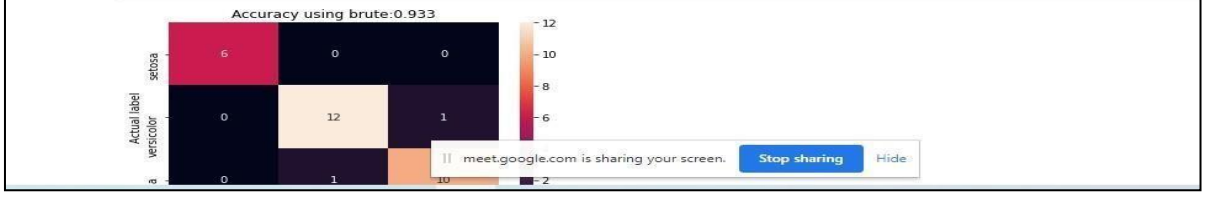
In [17]:
```
cv_scores = []
neighbors = list(np.arange(3,50,2))
for n in neighbors:
    knn = KNeighborsClassifier(n_neighbors = n,algorithm = 'brute')

    cross_val = cross_val_score(knn,x_train,y_train,cv = 5 , scoring = 'accuracy')
    cv_scores.append(cross_val.mean())

error = [1-x for x in cv_scores]
optimal_n = neighbors[ error.index(min(error)) ]
knn_optimal = KNeighborsClassifier(n_neighbors = optimal_n,algorithm = 'brute')
knn_optimal.fit(x_train,y_train)
pred = knn_optimal.predict(x_test)
acc = accuracy_score(y_test,pred)*100
print("The accuracy for optimal k = {0} using brute is {1}".format(optimal_n,acc))
```

```
The accuracy for optimal k = 7 using brute is 96.66666666666667
```

In [18]:
```
print("classification_report using brute force")
print(classification_report(y_test,pred))
```

```
classification_report using brute force
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         6
Iris-versicolor       1.00      0.92      0.96        13
 Iris-virginica       0.92      1.00      0.96        11

       accuracy                           0.97        30
      macro avg       0.97      0.97      0.97        30
   weighted avg       0.97      0.97      0.97        30
```

In [19]:
```
clf = SVC(kernel = 'linear').fit(x_train,y_train)
clf.predict(x_train)
y_pred = clf.predict(x_test)
# Creates a confusion matrix
cm = confusion_matrix(y_test, y_pred)
# Transform to df for easier plotting
cm_df = pd.DataFrame(cm,
                     index = ['setosa','versicolor','virginica'],
                     columns = ['setosa','versicolor','virginica'])

sns.heatmap(cm_df, annot=True)
plt.title('Accuracy using brute:{0:.3f}'.format(accuracy_score(y_test, y_pred)))
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
plt.show()
```



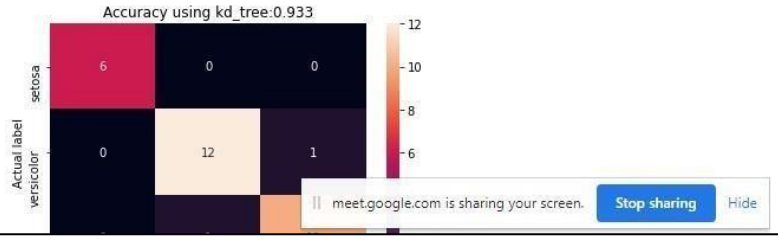
In [20]:
```
for n in neighbors:
    knn = KNeighborsClassifier(n_neighbors = n,algorithm = 'kd_tree')

    cross_val = cross_val_score(knn,x_train,y_train,cv = 5 , scoring = 'accuracy')
    cv_scores.append(cross_val.mean())

error = [1-x for x in cv_scores]
optimal_n = neighbors[ error.index(min(error)) ]
knn_optimal = KNeighborsClassifier(n_neighbors = optimal_n,algorithm = 'kd_tree')
knn_optimal.fit(x_train,y_train)
pred = knn_optimal.predict(x_test)
acc = accuracy_score(y_test,pred)*100
print("The accuracy for optimal k = {0} using kd-tree is {1}".format(optimal_n,acc))
```

```
The accuracy for optimal k = 7 using kd-tree is 96.66666666666667
```

In [21]:
```
print("classification_report using kd-tree")
print(classification_report(y_test,pred))
```

```
classification_report using kd-tree
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         6
Iris-versicolor       1.00      0.92      0.96        13
 Iris-virginica       0.92      1.00      0.96        11

       accuracy                           0.97        30
      macro avg       0.97
   weighted avg       0.97
```

In [22]:
```
clf = SVC(kernel = 'linear').fit(x_train,y_train)
clf.predict(x_train)
y_pred = clf.predict(x_test)
# Creates a confusion matrix
cm = confusion_matrix(y_test, y_pred)
# Transform to df for easier plotting
cm_df = pd.DataFrame(cm,
                     index = ['setosa','versicolor','virginica'],
                     columns = ['setosa','versicolor','virginica'])

sns.heatmap(cm_df, annot=True)
plt.title('Accuracy using kd_tree:{0:.3f}'.format(accuracy_score(y_test, y_pred)))
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
plt.show()
```



6a Implement the different Distance methods (Euclidean) with Prediction, Test Score and Confusion Matrix

In [1]:
```
#Import required libraries
#Import required libraries
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
#Load the dataset
url = "https://raw.githubusercontent.com/SharmaNatasha/Machine-Learning-using-Python/master/Datasets/IRIS.csv"
df = pd.read_csv(url)
#quick look into the data
df.head(5)
#Separate data and label
x = df.iloc[:,1:4]
y = df.iloc[:,4]
#Prepare data for classification process
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=0)
```

In [2]:
```
#Create a model
KNN_Classifier = KNeighborsClassifier(n_neighbors = 6, p = 2, metric='minkowski')
```

In [3]:
```
#Train the model
KNN_Classifier.fit(x_train, y_train)
#Let's predict the classes for test data
pred_test = KNN_Classifier.predict(x_test)
```

In [4]:
```
import numpy as np
import pandas as pd
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
#Load the dataset
url = "https://raw.githubusercontent.com/SharmaNatasha/Machine-Learning-using-Python/master/Datasets/IRIS.csv"
df = pd.read_csv(url)
#quick look into the data
df.head(5)
#Separate data and label
x = df.iloc[:,1:4].values
#Creating the kmeans classifier
KMeans_Cluster = KMeans(n_clusters = 3)
y_class = KMeans_Cluster.fit_predict(x)
```

In [5]:
```
import math
import numpy as np
import pandas as pd
import matplotlib.pyplot as pyplot
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer()
corpus = [
 'the brown fox jumped over the brown dog',
 'the quick brown fox',
 'the brown brown dog',
 'the fox ate the dog'
]
query = ["brown"]
X = vectorizer.fit_transform(corpus)
Y = vectorizer.transform(query)
```

In [6]:
```
cosine_similarity(Y, X.toarray())
```

Out[6]:
```
array([[0.54267123, 0.44181486, 0.84003859, 0.        ]])
```

6b Implement the classification model using clustering for the following techniques with K means clustering with Prediction, Test Score and Confusion Matrix.

In [1]:
```
# read in the iris data
from sklearn.datasets import load_iris
iris = load_iris()

# create X (features) and y (response)
X = iris.data
y = iris.target
```

In [2]:
```
# import the class
from sklearn.linear_model import LogisticRegression

# instantiate the model (using the default parameters)
logreg = LogisticRegression()

# fit the model with data
logreg.fit(X, y)

# predict the response values for the observations in X
logreg.predict(X)
```

```
C:\Users\Hina\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:762: ConvergenceWarning: lbfgs failed to converg
(status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[2]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 2, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 1, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

In [3]:
```
# store the predicted response values
y_pred = logreg.predict(X)

# check how many predictions were generated
len(y_pred)
```

Out[3]:
```
150
```

In [4]:
```
# compute classification accuracy for the logistic regression model
from sklearn import metrics

print(metrics.accuracy_score(y, y_pred))
```

```
0.9733333333333334
```

In [5]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X, y)
y_pred = knn.predict(X)
print(metrics.accuracy_score(y, y_pred))
```

```
0.9666666666666667
```

In [6]:
```
knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(X, y)
y_pred = knn.predict(X)
print(metrics.accuracy_score(y, y_pred))
```

```
1.0
```

In [7]:
```
# print the shapes of X and y
# X is our features matrix with 150 x 4 dimension
print(X.shape)
# y is our response vector with 150 x 1 dimension
print(y.shape)
```

```
(150, 4)
(150,)
```

In [9]:
```
# STEP 1: split X and y into training and testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=4)
```

In [10]:
```
# print the shapes of the new X objects
print(X_train.shape)
print(X_test.shape)
```

```
(90, 4)
(60, 4)
```

In [11]:
```
# print the shapes of the new y objects
print(y_train.shape)
print(y_test.shape)
(90,)
```

```
(90,)
(60,)
```

Out[11]:
```
(90,)
```

In [12]:
```
# STEP 2: train the model on the training set
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

Out[12]:
```
LogisticRegression()
```

In [13]:
```
# STEP 3: make predictions on the testing set
y_pred = logreg.predict(X_test)

# compare actual response values (y_test) with predicted response values (y_pred)
print(metrics.accuracy_score(y_test, y_pred))
```

```
0.9666666666666667
```

In [14]:
```
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print(metrics.accuracy_score(y_test, y_pred))
```

```
0.9666666666666667
```

In [15]:
```
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print(metrics.accuracy_score(y_test, y_pred))
```

```
0.9666666666666667
```

In [16]:
```
# try K=1 through K=25 and record testing accuracy
k_range = range(1, 26)

# We can create Python dictionary using [] or dict()
scores = []
```

```
# We use a loop through the range 1 to 26
# We append the scores in the dictionary
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    scores.append(metrics.accuracy_score(y_test, y_pred))

print(scores)
```

```
[0.95, 0.95, 0.9666666666666667, 0.9666666666666667, 0.9666666666666667, 0.9833333333333333, 0.9833333333333333, 0.9833333333333333, 0.9833333333333333, 0.9833333333333333, 0.9833333333333333, 0.9833333333333333, 0.9833333333333333, 0.9833333333333333, 0.9833333333333333, 0.9666666666666667, 0.9833333333333333, 0.9666666666666667, 0.9666666666666667, 0.9666666666666667, 0.95, 0.95]
```

In [17]:
```
# import Matplotlib (scientific plotting library)
import matplotlib.pyplot as plt

# allow plots to appear within the notebook
%matplotlib inline

# plot the relationship between K and testing accuracy
# plt.plot(x_axis, y_axis)
plt.plot(k_range, scores)
plt.xlabel('Value of K for KNN')
plt.ylabel('Testing Accuracy')
```

Out[17]: Text(0, 0.5, 'Testing Accuracy')

In [18]:
```
# instantiate the model with the best known parameters
knn = KNeighborsClassifier(n_neighbors=11)

# train the model with X and y (not X_train and y_train)
knn.fit(X, y)

# make a prediction for an out-of-sample observation
knn.predict([3, 5, 4, 2])
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-18-9d289456709c> in <module>
      6
      7 # make a prediction for an out-of-sample observation
----> 8 knn.predict([3, 5, 4, 2])

~\anaconda3\lib\site-packages\sklearn\neighbors\_classification.py in predict(self, X)
    171             Class labels for each data sample.
    172         """
--> 173         X = check_array(X, accept_sparse='csr')
    174
    175         neigh_dist, neigh_ind = self.kneighbors(X)

~\anaconda3\lib\site-packages\sklearn\utils\validation.py in inner_f(*args, **kwargs)
```

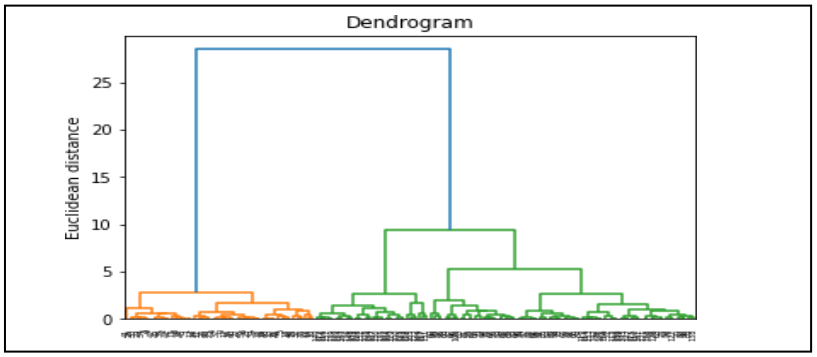
```
ValueError: Expected 2D array, got 1D array instead:
array=[3 5 4 2].
Reshape your data either using array.reshape(-1, 1) if your data has a single feature or array.reshape(1, -1) if it contains a
single sample.
```

7a Implement the classification model using clustering for the following techniques with hierarchical clustering with Prediction, Test Score and Confusion Matrix

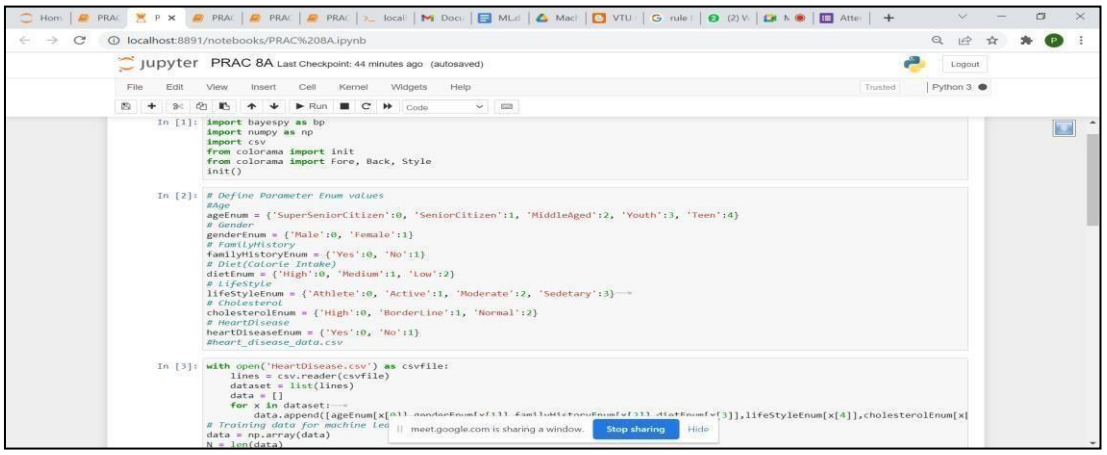
In [1]:
```
#Importing required libraries

from sklearn.datasets import load_iris
from sklearn.cluster import AgglomerativeClustering
import numpy as np
import matplotlib.pyplot as plt


#Getting the data ready

data = load_iris()
df = data.data
#Selecting certain features based on which clustering is done
df = df[:,1:3]
```

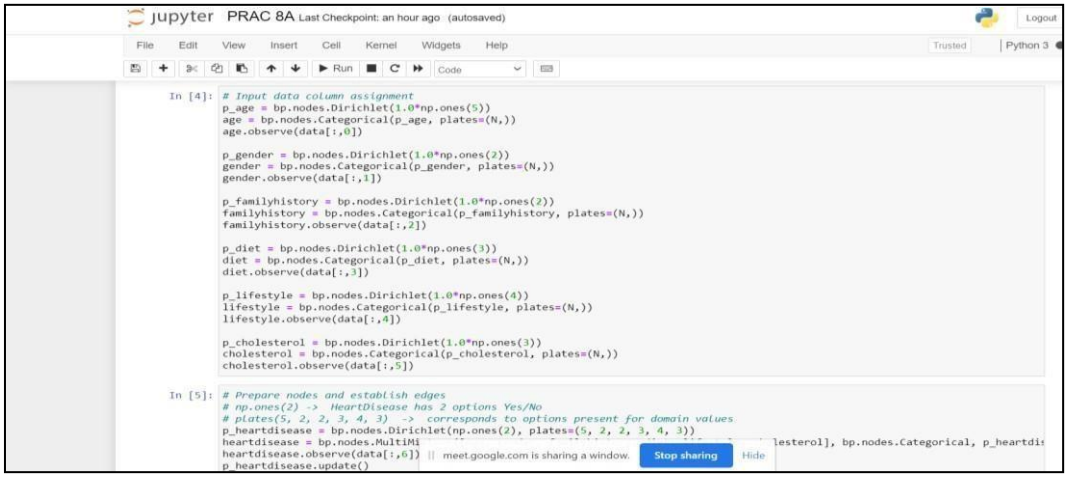
In [2]:
```
#Creating the model
agg_clustering = AgglomerativeClustering(n_clusters = 3, affinity = 'euclidean', linkage = 'ward')
#predicting the labels
labels = agg_clustering.fit_predict(df)
#Plotting the results
plt.figure(figsize = (8,5))
plt.scatter(df[labels == 0 , 0] , df[labels == 0 , 1] , c = 'red')
plt.scatter(df[labels == 1 , 0] , df[labels == 1 , 1] , c = 'blue')
plt.scatter(df[labels == 2 , 0] , df[labels == 2 , 1] , c = 'green')
plt.show()
```

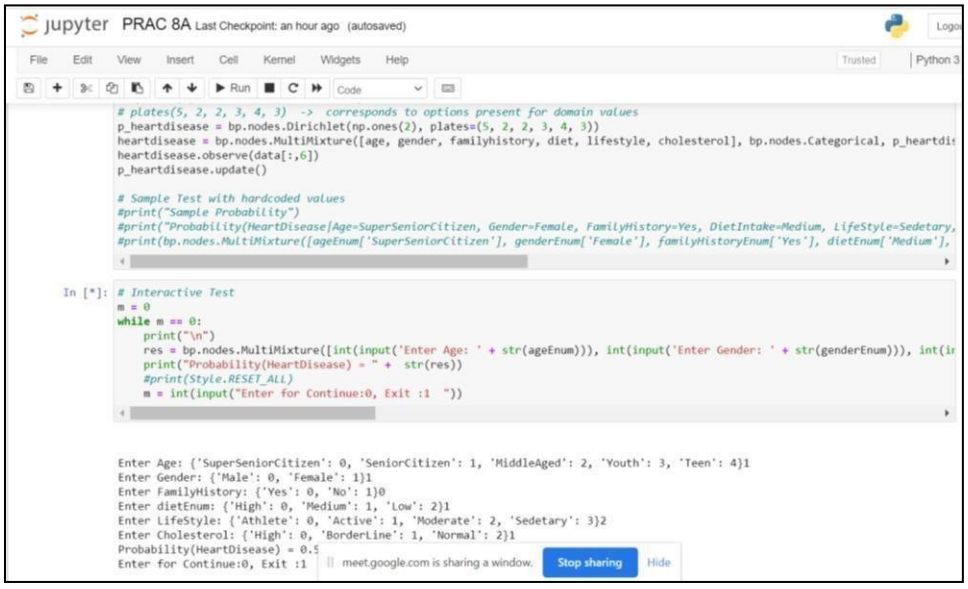
In [3]:
```
#Importing libraries
from sklearn.datasets import load_iris
from sklearn.cluster import AgglomerativeClustering
import numpy as np
import matplotlib.pyplot as plt
from scipy.cluster.hierarchy import dendrogram , linkage

#Getting the data ready

data = load_iris()
df = data.data
#Selecting certain features based on which clustering is done
df = df[:,1:3]

#Linkage Matrix
Z = linkage(df, method = 'ward')

#plotting dendrogram
dendro = dendrogram(Z)
plt.title('Dendrogram')
plt.ylabel('Euclidean distance')
plt.show()
```



8a. Write a program to construct a Bayesian network considering medical data. Use this model to demonstrate the diagnosis of heart patients using standard Heart Disease Data Set







b. Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs

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Run Code

In [1]:
```
from math import ceil
import numpy as np
from scipy import linalg
```

In [2]:
```
def lowess(x, y, f, iterations):
    n = len(x)
    r = int(ceil(f * n))
    h = [np.sort(np.abs(x - x[i]))[r] for i in range(n)]
    w = np.clip(np.abs((x[:, None] - x[None, :]) / h), 0.0, 1.0)
    w = (1 - w ** 3) ** 3
    yest = np.zeros(n)
    delta = np.ones(n)
    for iteration in range(iterations):
        for i in range(n):
            weights = delta * w[:, i]
            b = np.array([np.sum(weights * y), np.sum(weights * y * x)])
            A = np.array([[np.sum(weights), np.sum(weights * x)],[np.sum(weights * x), np.sum(weights * x * x)]])
            beta = linalg.solve(A, b)
            yest[i] = beta[0] + beta[1] * x[i]

        residuals = y - yest
        s = np.median(np.abs(residuals))
        delta = np.clip(residuals / (6.0 * s), -1, 1)
        delta = (1 - delta ** 2) ** 2

    return yest
```

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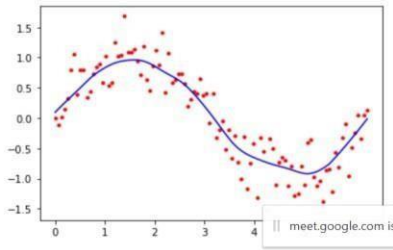
Run Code

In [3]:
```
import math
n = 100
x = np.linspace(0, 2 * math.pi, n)
y = np.sin(x) + 0.3 * np.random.randn(n)
f =0.25
iterations=3
yest = lowess(x, y, f, iterations)

import matplotlib.pyplot as plt
plt.plot(x,y,"r.")
plt.plot(x,yest,"b-")
```

Out[3]:
```
[<matplotlib.lines.Line2D at 0x1fdb041eac0>]
```



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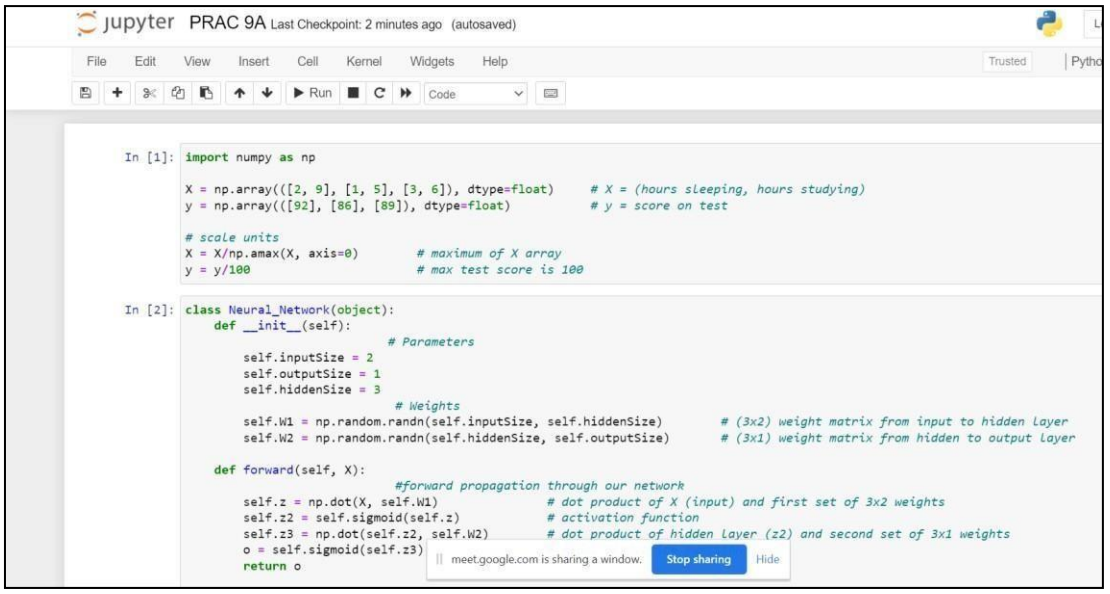
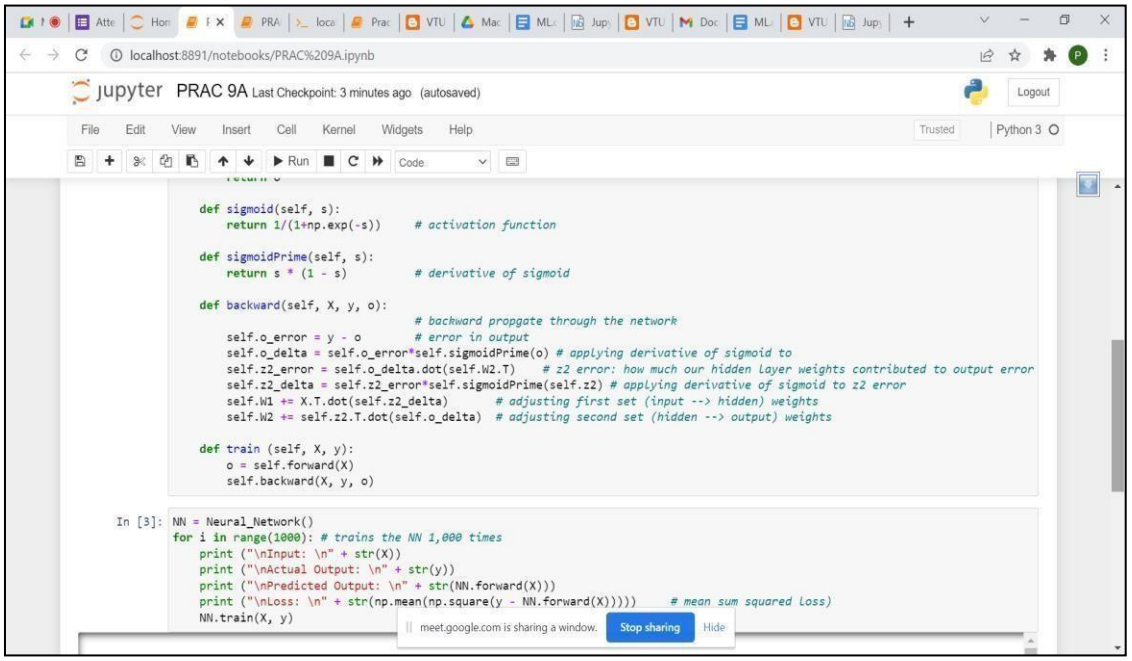
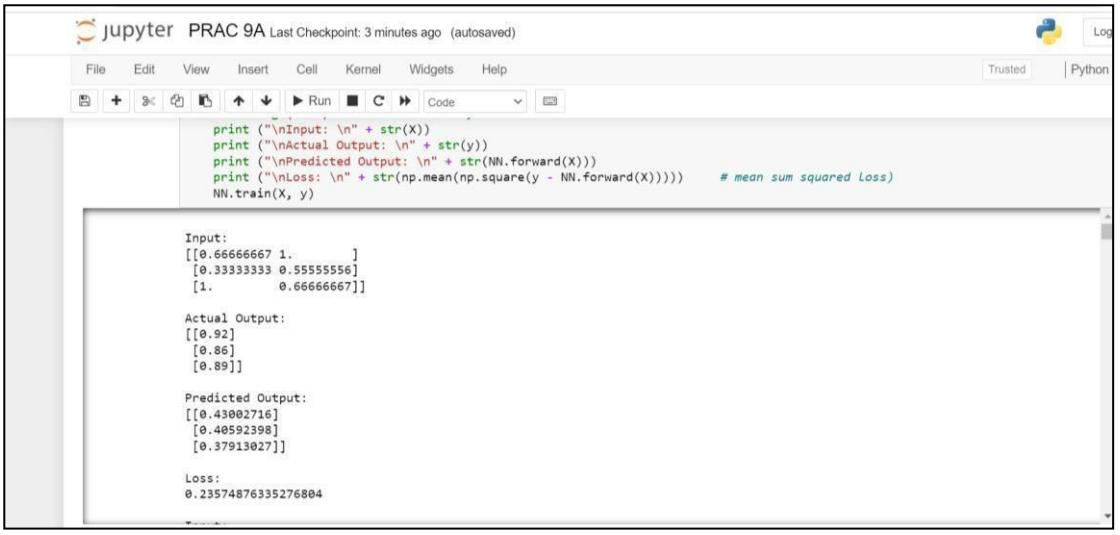
9A. Build an Artificial Neural Network by implementing the Backpropagation algorithm and test the same using appropriate data sets.






jupyter PRAC 9A Last Checkpoint: 3 minutes ago (autosaved)
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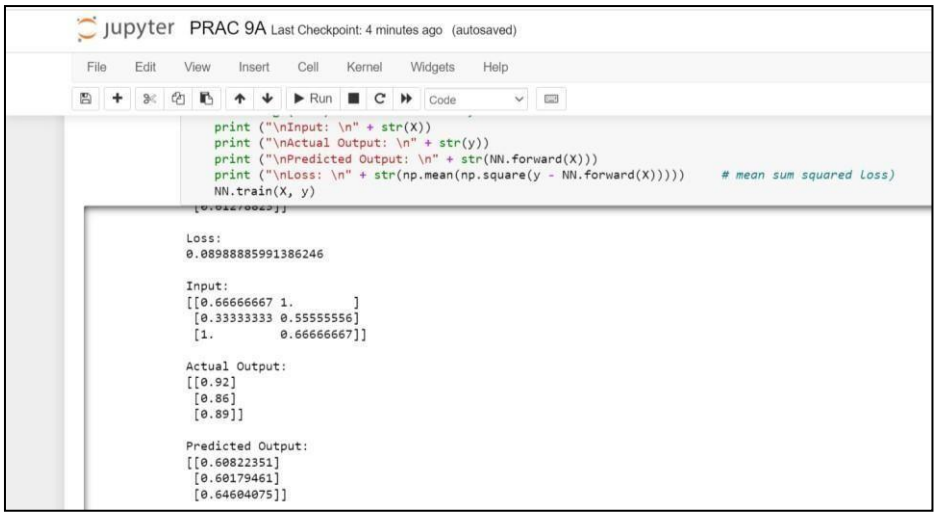
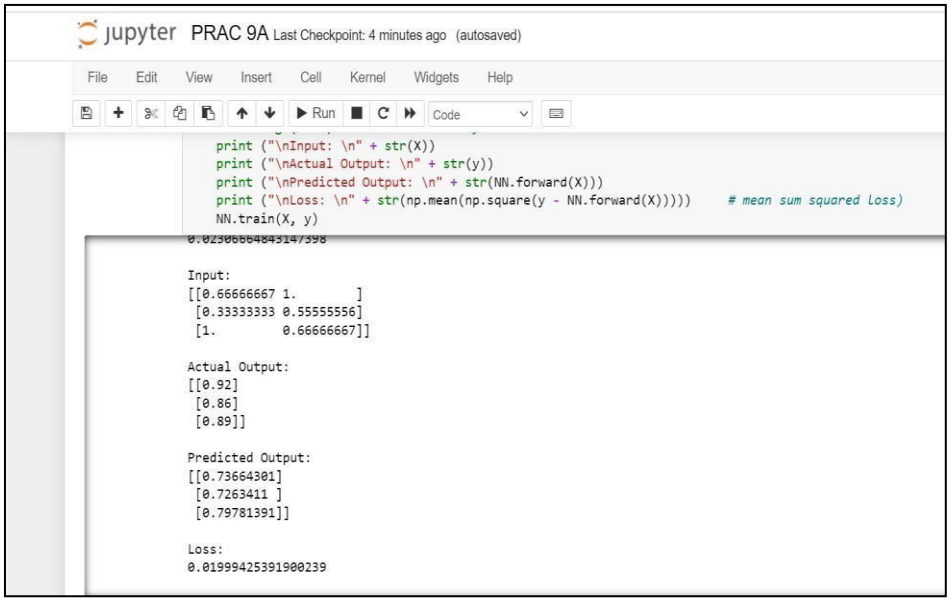
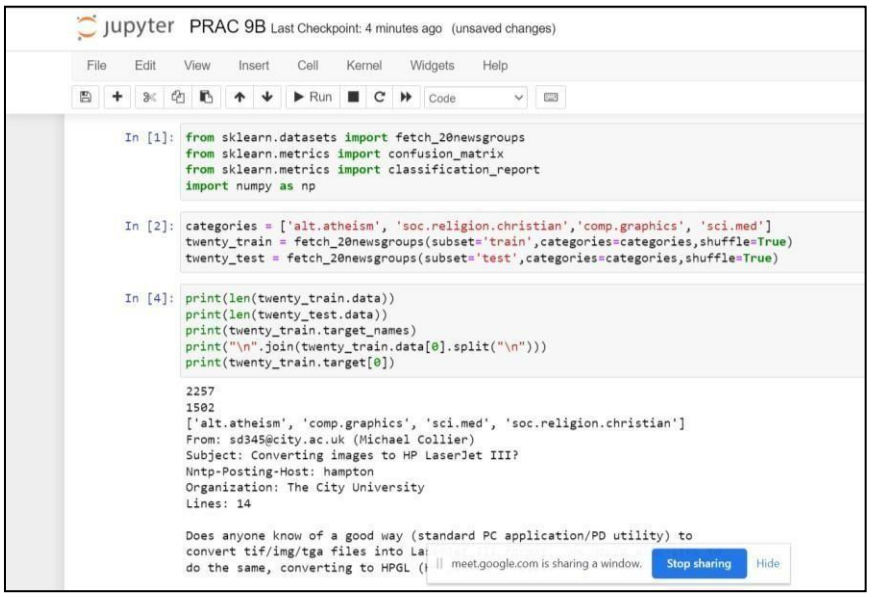
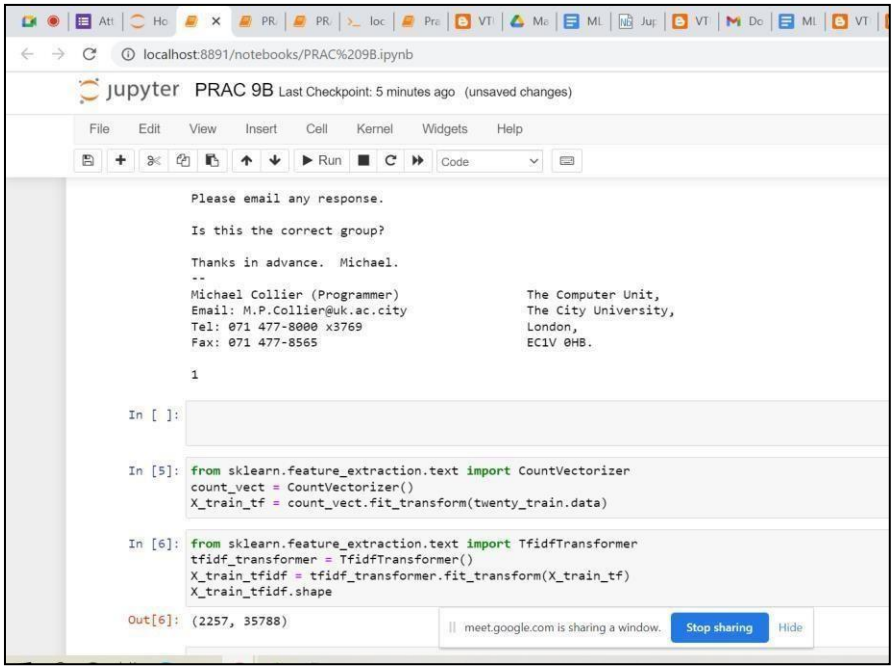
Trusted
Python
Run
Code
print ("\nInput: \n" + str(X))
print ("\nActual Output: \n" + str(y))
print ("\nPredicted Output: \n" + str(NN.forward(X)))
print ("\nLoss: \n" + str(np.mean(np.square(y - NN.forward(X)))))
# mean sum squared loss)
NN.train(X, y)
Input:
[[0.66666667 1.]
[0.33333333 0.55555556]
[1. 0.66666667]]
Actual Output:
[[0.92]
[0.86]
[0.89]]
Predicted Output:
[[0.43002716]
[0.40592398]
[0.37913027]]
Loss:
0.23574876335276804

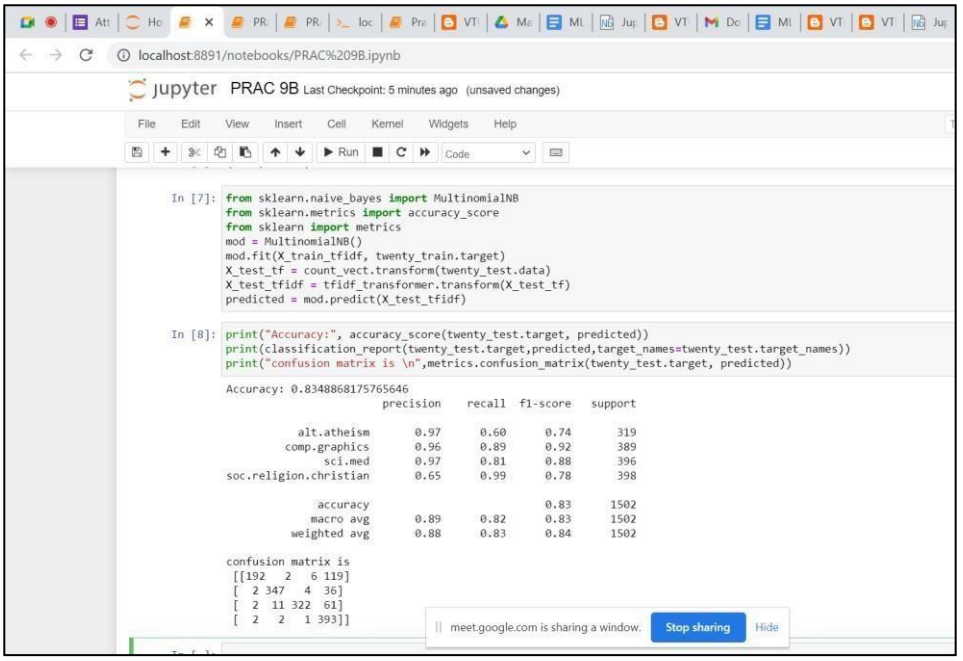

jupyter PRAC 9A Last Checkpoint: 4 minutes ago (autosaved)
File Edit View Insert Cell Kernel Widgets Help
Run
Code
print ("\nInput: \n" + str(X))
print ("\nActual Output: \n" + str(y))
print ("\nPredicted Output: \n" + str(NN.forward(X)))
print ("\nLoss: \n" + str(np.mean(np.square(y - NN.forward(X)))))
# mean sum squared loss)
NN.train(X, y)
Loss:
0.08988885991386246
Input:
[[0.66666667 1.]
[0.33333333 0.55555556]
[1. 0.66666667]]
Actual Output:
[[0.92]
[0.86]
[0.89]]
Predicted Output:
[[0.60822351]
[0.60179461]
[0.64604075]]


jupyter PRAC 9A Last Checkpoint: 4 minutes ago (autosaved)
File Edit View Insert Cell Kernel Widgets Help
Run
Code
print ("\nInput: \n" + str(X))
print ("\nActual Output: \n" + str(y))
print ("\nPredicted Output: \n" + str(NN.forward(X)))
print ("\nLoss: \n" + str(np.mean(np.square(y - NN.forward(X)))))
# mean sum squared loss)
NN.train(X, y)
Input:
[[0.66666667 1.]
[0.33333333 0.55555556]
[1. 0.66666667]]
Actual Output:
[[0.92]
[0.86]
[0.89]]
Predicted Output:
[[0.73664301]
[0.7263411]
[0.79781391]]
Loss:
0.01999425391900239

9B. ASSUMING A SET OF DOCUMENTS THAT NEED TO BE CLASSIFIED, USE THE NAÏVE BAYESIAN CLASSIFIER MODEL TO PERFORM THIS TASK. BUILT-IN JAVA CLASSES/API CAN BE USED TO WRITE THE PROGRAM. CALCULATE THE ACCURACY, PRECISION, AND RECALL FOR YOUR DATA SET.






localhost:8891/notebooks/PRAC%209B.ipynb
jupyter PRAC 9B Last Checkpoint: 5 minutes ago (unsaved changes)
File Edit View Insert Cell Kernel Widgets Help
Run
Code
In [7]:
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score
from sklearn import metrics
mod = MultinomialNB()
mod.fit(X_train_tfidf, twenty_train.target)
X_test_tf = count_vect.transform(twenty_test.data)
X_test_tfidf = tfidf_transformer.transform(X_test_tf)
predicted = mod.predict(X_test_tfidf)
In [8]:
print("Accuracy:", accuracy_score(twenty_test.target, predicted))
print(classification_report(twenty_test.target,predicted,target_names=twenty_test.target_names))
print("confusion matrix is \n",metrics.confusion_matrix(twenty_test.target, predicted))
Accuracy: 0.8348868175765646
precision recall f1-score support
alt.atheism 0.97 0.60 0.74 319
comp.graphics 0.96 0.89 0.92 389
sci.med 0.97 0.81 0.88 396
soc.religion.christian 0.65 0.99 0.78 398
accuracy 0.83 1502
macro avg 0.89 0.82 0.83 1502
weighted avg 0.88 0.83 0.84 1502
confusion matrix is
[[192 2 6 119]
[2 347 4 36]
[2 11 322 61]
[2 2 1 393]]
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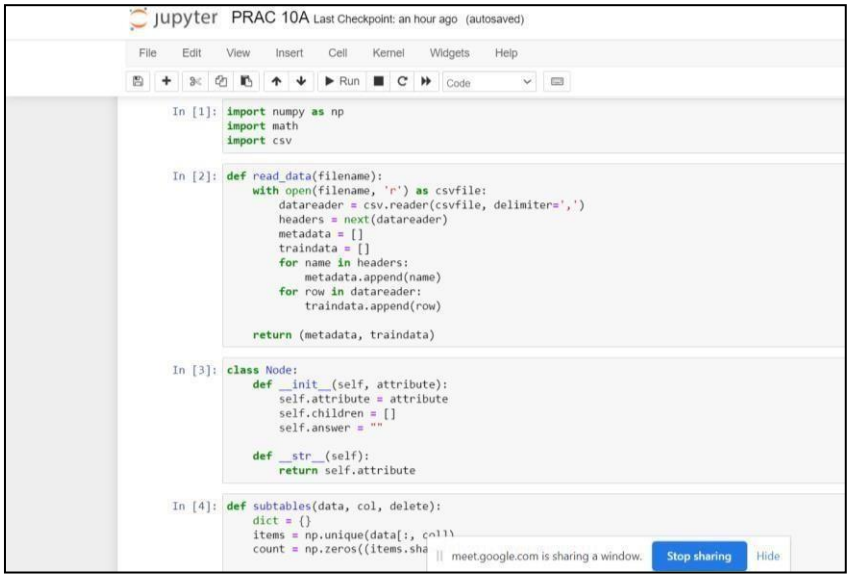
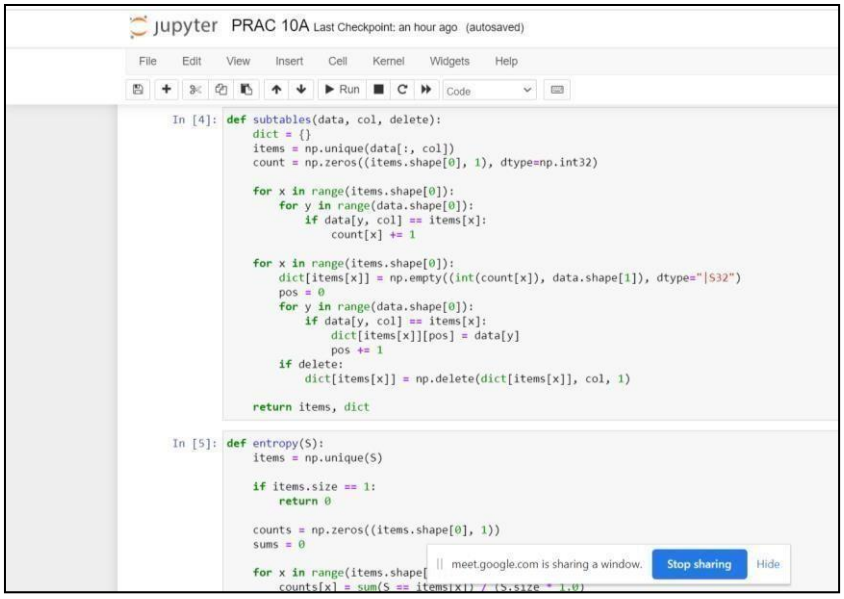
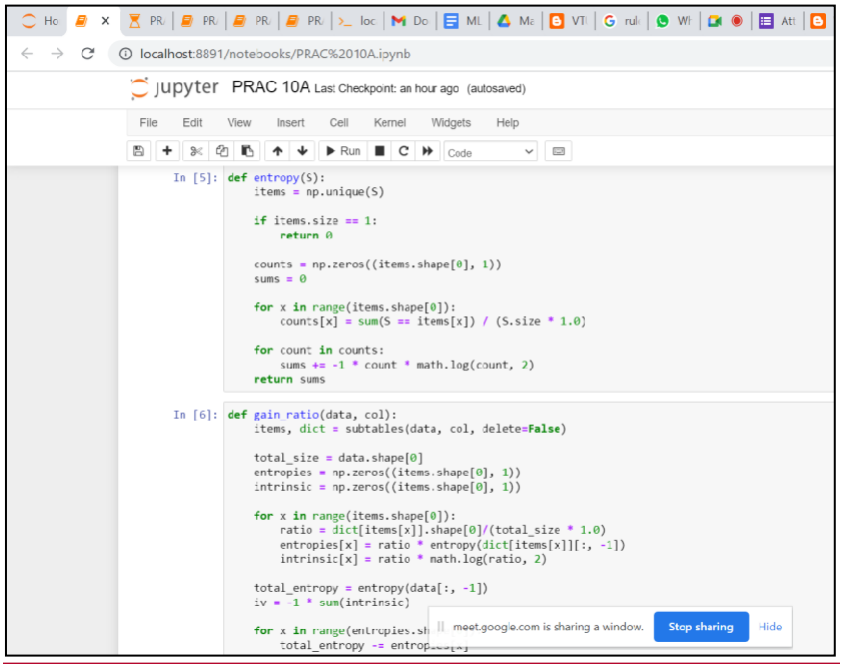
10A . Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample.



```
In [1]: import numpy as np
        import math
        import csv

In [2]: def read_data(filename):
            with open(filename, 'r') as csvfile:
                datareader = csv.reader(csvfile, delimiter=',')
                headers = next(datareader)
                metadata = []
                traindata = []
                for name in headers:
                    metadata.append(name)
                for row in datareader:
                    traindata.append(row)

            return (metadata, traindata)

In [3]: class Node:
            def __init__(self, attribute):
                self.attribute = attribute
                self.children = []
                self.answer = ""

            def __str__(self):
                return self.attribute

In [4]: def subtables(data, col, delete):
            dict = {}
            items = np.unique(data[:, col])
            count = np.zeros((items.sha
```

```
In [4]: def subtables(data, col, delete):
            dict = {}
            items = np.unique(data[:, col])
            count = np.zeros((items.shape[0], 1), dtype=np.int32)

            for x in range(items.shape[0]):
                for y in range(data.shape[0]):
                    if data[y, col] == items[x]:
                        count[x] += 1

            for x in range(items.shape[0]):
                dict[items[x]] = np.empty((int(count[x]), data.shape[1]), dtype="|S32")
                pos = 0
                for y in range(data.shape[0]):
                    if data[y, col] == items[x]:
                        dict[items[x]][pos] = data[y]
                        pos += 1
                if delete:
                    dict[items[x]] = np.delete(dict[items[x]], col, 1)

            return items, dict

In [5]: def entropy(S):
            items = np.unique(S)

            if items.size == 1:
                return 0

            counts = np.zeros((items.shape[0], 1))
            sums = 0

            for x in range(items.shape[
                counts[x] = sum(S == items[x]) / (S.size * 1.0)
```


localhost:8891/notebooks/PRAC%2010A.ipynb
jupyter PRAC 10A Last Checkpoint: an hour ago (autosaved)
File Edit View Insert Cell Kernel Widgets Help
Run Code
In [5]:
def entropy(S):
items = np.unique(S)
if items.size == 1:
return 0
counts = np.zeros((items.shape[0], 1))
sums = 0
for x in range(items.shape[0]):
counts[x] = sum(S == items[x]) / (S.size * 1.0)
for count in counts:
sums += -1 * count * math.log(count, 2)
return sums
In [6]:
def gain_ratio(data, col):
items, dict = subtables(data, col, delete=False)
total_size = data.shape[0]
entropies = np.zeros((items.shape[0], 1))
intrinsic = np.zeros((items.shape[0], 1))
for x in range(items.shape[0]):
ratio = dict[items[x]].shape[0]/(total_size * 1.0)
entropies[x] = ratio * entropy(dict[items[x]][:, -1])
intrinsic[x] = ratio * math.log(ratio, 2)
total_entropy = entropy(data[:, -1])
iv = -1 * sum(intrinsic)
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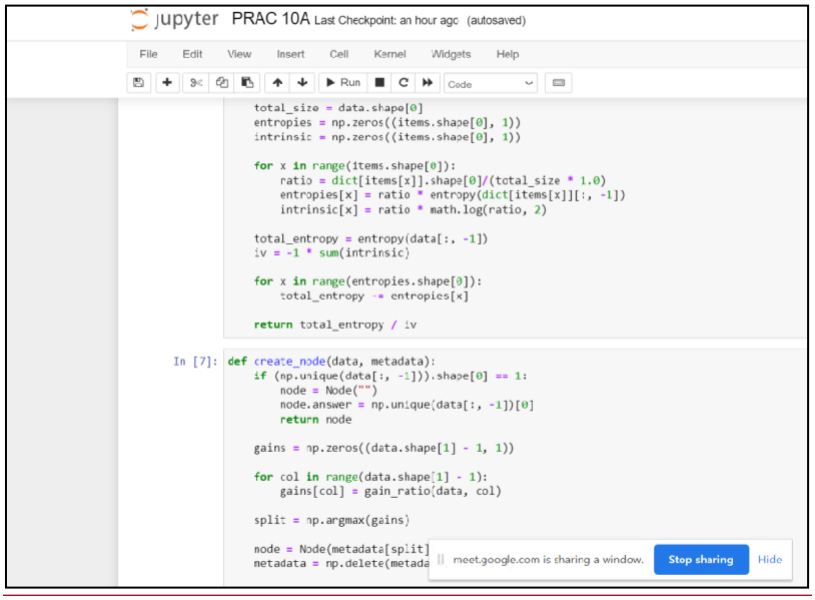
jupyter PRAC 10A Last Checkpoint: an hour ago (autosaved)
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Run Code
total_size = data.shape[0]
entropies = np.zeros((items.shape[0], 1))
intrinsic = np.zeros((items.shape[0], 1))
for x in range(items.shape[0]):
ratio = dict[items[x]].shape[0]/(total_size * 1.0)
entropies[x] = ratio * entropy(dict[items[x]][:, -1])
intrinsic[x] = ratio * math.log(ratio, 2)
total_entropy = entropy(data[:, -1])
iv = -1 * sum(intrinsic)
for x in range(entropies.shape[0]):
total_entropy -= entropies[x]
return total_entropy / iv
In [7]:
def create_node(data, metadata):
if (np.unique(data[:, -1])).shape[0] == 1:
node = Node("")
node.answer = np.unique(data[:, -1])[0]
return node
gains = np.zeros((data.shape[1] - 1, 1))
for col in range(data.shape[1] - 1):
gains[col] = gain_ratio(data, col)
split = np.argmax(gains)
node = Node(metadata[split]
metadata = np.delete(metada
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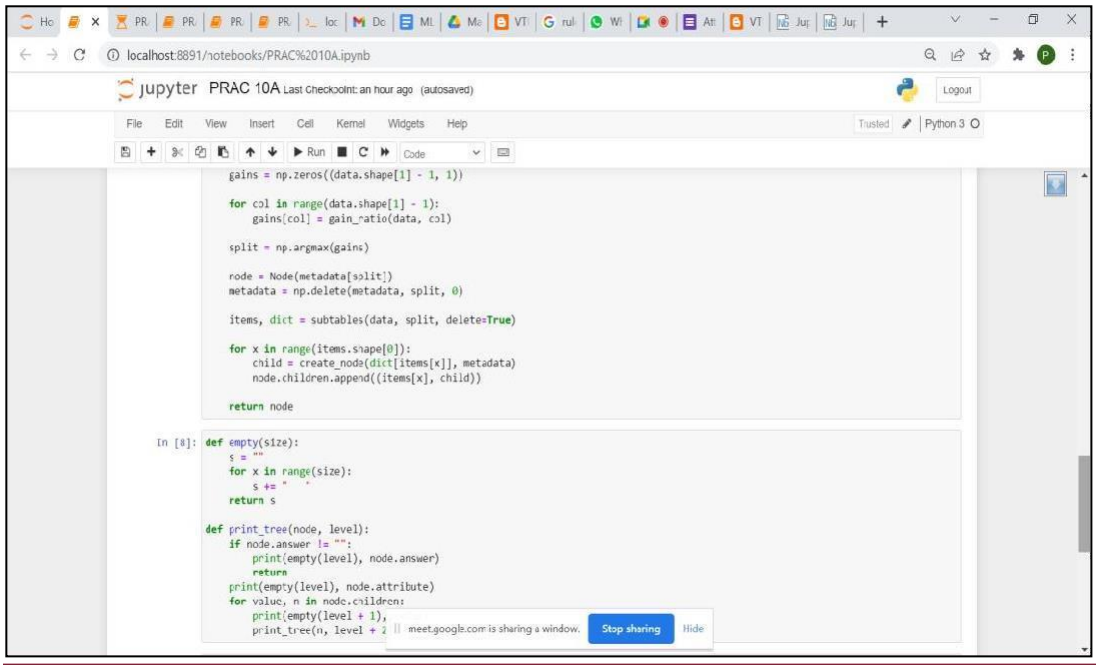
localhost:8891/notebooks/PRAC%2010A.ipynb
jupyter PRAC 10A Last Checkpoint: an hour ago (autosaved)
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Trusted Python 3
Run Code
gains = np.zeros((data.shape[1] - 1, 1))
for col in range(data.shape[1] - 1):
gains[col] = gain_ratio(data, col)
split = np.argmax(gains)
node = Node(metadata[split])
metadata = np.delete(metadata, split, 0)
items, dict = subtables(data, split, delete=True)
for x in range(items.shape[0]):
child = create_node(dict[items[x]], metadata)
node.children.append((items[x], child))
return node
In [8]:
def empty(size):
s = ""
for x in range(size):
s += " "
return s
def print_tree(node, level):
if node.answer != "":
print(empty(level), node.answer)
return
print(empty(level), node.attribute)
for value, n in node.children:
print(empty(level + 1),
print_tree(n, level + 2
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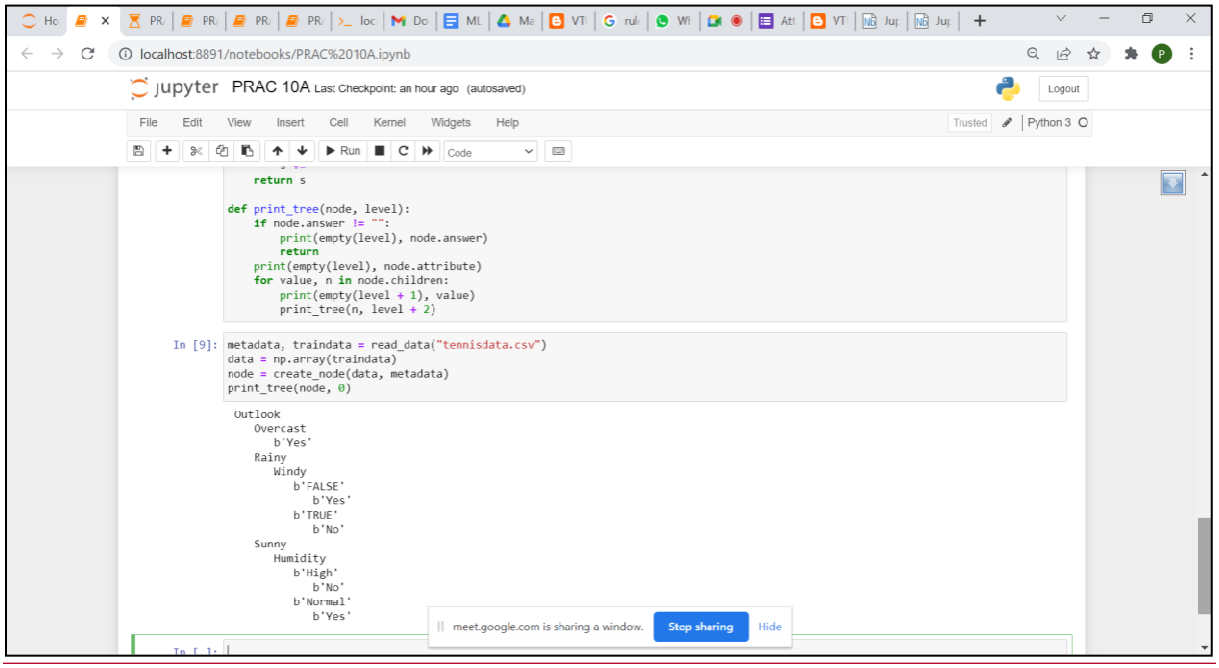
localhost:8891/notebooks/PRAC%2010A.ipynb
jupyter PRAC 10A Last Checkpoint: an hour ago (autosaved)
Logout
File Edit View Insert Cell Kernel Widgets Help
Trusted Python 3
Run Code
return s
def print_tree(node, level):
if node.answer != "":
print(empty(level), node.answer)
return
print(empty(level), node.attribute)
for value, n in node.children:
print(empty(level + 1), value)
print_tree(n, level + 2)
In [9]:
metadata, traindata = read_data("tennisdata.csv")
data = np.array(traindata)
node = create_node(data, metadata)
print_tree(node, 0)
Outlook
Overcast
b'Yes'
Rainy
Windy
b'FALSE'
b'Yes'
b'TRUE'
b'No'
Sunny
Humidity
b'High'
b'No'
b'Normal'
b'Yes'
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