Department of Computer Science and Engineering (Data Science)

Subject: Machine Learning – I (DJ19DSC402)

AY: 2021-22

Experiment 4 (Naïve Bayes Classifier)

Name: Dev Patel SAP ID: 60009200016

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Aim: Implement Naïve Bayes Classifier on a given Dataset.

Theory:

Naïve Bayes Classifier Algorithm

- Naïve Bayes algorithm is a supervised learning algorithm, which is based on **Bayes theorem** and used for solving classification problems.
- o It is mainly used in *text classification* that includes a high-dimensional training dataset.
- Naïve Bayes Classifier is one of the simple and most effective Classification algorithms which helps in building the fast machine learning models that can make quick predictions.
- o It is a probabilistic classifier, which means it predicts on the basis of the probability of an object.
- Some popular examples of Naïve Bayes Algorithm are spam filtration, Sentimental analysis, and classifying articles.
 - The Naïve Bayes algorithm is comprised of two words Naïve and Bayes, which can be described as:
- Naïve: It is called Naïve because it assumes that the occurrence of a certain feature is independent of the occurrence of other features. Such as if the fruit is identified on the bases of colour, shape, and taste, then red, spherical, and sweet fruit is recognized as an apple. Hence each feature individually contributes to identify that it is an apple without depending on each other.
- Bayes: It is called Bayes because it depends on the principle of Bayes' Theorem.
 Bayes' Theorem:
- Bayes' theorem is also known as Bayes' Rule or Bayes' law, which is used to determine the probability of a hypothesis with prior knowledge. It depends on the conditional probability.
- The formula for Bayes' theorem is given as:

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

Where,

P(A|B) is Posterior probability: Probability of hypothesis A on the observed event B.

P(B|A) is Likelihood probability: Probability of the evidence given that the probability of a hypothesis is true.

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P(A) is **Prior Probability**: Probability of hypothesis before observing the evidence.

P(B) is Marginal Probability: Probability of Evidence.

Types of Naïve Bayes Model:

There are three types of Naive Bayes Model, which are given below:

Gaussian: The Gaussian model assumes that features follow a normal distribution. This means if predictors take continuous values instead of discrete, then the model assumes that these values are sampled from the Gaussian distribution.

- Multinomial: The Multinomial Naïve Bayes classifier is used when the data is multinomial distributed. It is primarily used for document classification problems, it means a particular document belongs to which category such as Sports, Politics, education, etc.
 - The classifier uses the frequency of words for the predictors.
- Bernoulli: The Bernoulli classifier works similar to the Multinomial classifier, but the predictor variables are the independent Booleans variables. Such as if a particular word is present or not in a document. This model is also famous for document classification tasks.

Lab Assignments to complete in this session:

Use the given dataset and perform the following tasks:

Dataset 1: Breastcancer.csv

Dataset 2: Social_Network_Ads.csv

Dataset 3: emails.csv

Dataset 4: German_credit_score.csv

- 1. Perform required pre-processing on Dataset 1 and fit a Naïve Bayes classifier built from scratch. Evaluate the f1 score of the classifier.
- 2. Using sklearn library fit a Naïve Bayes classifier on Dataset 2 and Dataset 4.

Code and Output:

```
In [1]:
```

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import sklearn.preprocessing
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score , confusion_matrix, fl_score
%matplotlib inline
```

1. Perform required preprocessing on Dataset 1 and fit a Naïve Bayes classifier built from scratch and evaluate the f1 score of classifier.

```
In [2]:
```

```
brc = pd.read_csv('/content/sample_data/Breast_cancer_data.csv')
brc.head()
```

Out[2]:

	mean_radius	mean_texture	mean_perimeter	mean_area	mean_smoothness	diagnosis
0	17.99	10.38	122.80	1001.0	0.11840	0
1	20.57	17.77	132.90	1326.0	0.08474	0
2	19.69	21.25	130.00	1203.0	0.10960	0
3	11.42	20.38	77.58	386.1	0.14250	0
4	20.29	14.34	135.10	1297.0	0.10030	0

```
In [3]:
```

```
brc.isnull().sum()
```

Out[3]:

```
mean_radius 0
mean_texture 0
mean_perimeter 0
mean_area 0
mean_smoothness 0
diagnosis 0
dtype: int64
```

In [4]:

```
brc.duplicated().sum()
```

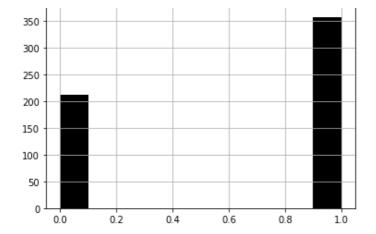
Out[4]:

0

EDA

```
In [5]:
```

```
brc["diagnosis"].hist(color = 'black')
Out[5]:
<matplotlib.axes. subplots.AxesSubplot at 0x7f0cefd1ced0>
```

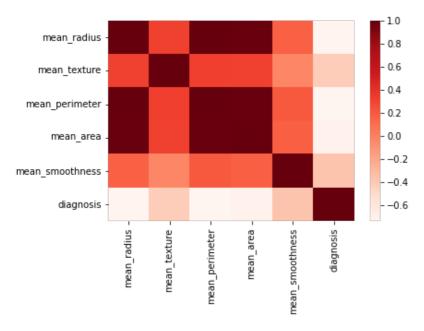


In [6]:

```
sns.heatmap(brc.corr(),cmap = 'Reds')
```

Out[6]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f0cefc1dc90>



In [7]:

```
brc = brc[["mean_radius", "mean_texture", "mean_smoothness", "diagnosis"]] #dropping corr
elated columns
brc.head()
```

Out[7]:

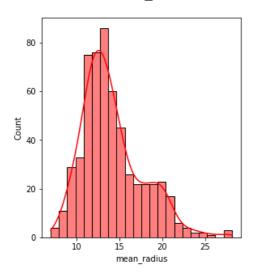
	mean_radius	mean_texture	mean_smoothness	diagnosis
0	17.99	10.38	0.11840	0
1	20.57	17.77	0.08474	0
2	19.69	21.25	0.10960	0
3	11.42	20.38	0.14250	0
4	20.29	14.34	0.10030	0

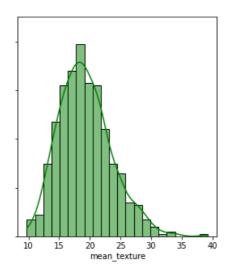
In [8]:

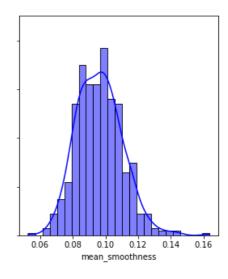
```
fig, axes = plt.subplots(1, 3, figsize=(15, 5), sharey=True)
sns.histplot(brc, ax=axes[0], x="mean_radius", color='r', kde=True)
sns.histplot(brc, ax=axes[1], x="mean_texture", color ='g', kde=True)
sns.histplot(brc, ax=axes[2], x="mean_smoothness", color='b', kde=True)
```

Out[8]:

\macptocttp.axcb._basptoco.twcbbasptoc ac oxitoccocbocto;







In [9]:

```
# Calculate P(Y=y) for all possible y

def calculate_prior(df, Y):
    classes = sorted(list(df[Y].unique()))
    prior = []
    for i in classes:
        prior.append(len(df[df[Y]==i])/len(df))
    return prior
```

In [10]:

```
# To Calculate P(X=x/Y=y) using Gaussian distribution

def calculate_likelihood_gaussian(df, feat_name, feat_val, Y, label):
    feat = list(df.columns)
    df = df[df[Y]==label]
    mean, std = df[feat_name].mean(), df[feat_name].std()
    p_x_given_y = (1 / (np.sqrt(2 * np.pi) * std)) * np.exp(-((feat_val-mean)**2 / (2 * std**2 )))
    return p_x_given_y
```

In [11]:

```
# To calculate P(X=x1|Y=y) P(X=x2|Y=y) ... P(X=xn|Y=y) * P(Y=y) for all y and to find the ma
ximum of all
def naive bayes gaussian(df, X, Y):
    features = list(df.columns)[:-1]
   prior = calculate prior(df, Y)
    Y pred = []
    for x in X:
        labels = sorted(list(df[Y].unique()))
        likelihood = [1] *len(labels)
        for j in range(len(labels)):
            for i in range(len(features)):
                likelihood[j] *= calculate likelihood gaussian(df, features[i], x[i], Y,
labels[j])
        post_prob = [1]*len(labels)
        for j in range(len(labels)):
            post prob[j] = likelihood[j] * prior[j]
        Y pred.append(np.argmax(post prob))
    return np.array(Y pred)
```

In [12]:

```
# Test Gaussian model
train, test = train_test_split(brc, test_size=.25, random_state=41)
```

```
X_test = test.iloc[:,:-1].values
Y_test = test.iloc[:,-1].values
Y_pred = naive_bayes_gaussian(train, X=X_test, Y="diagnosis")

print("Confusion matrix:\n", confusion_matrix(Y_test, Y_pred))
print("\nF1 score of the model =",f1_score(Y_test, Y_pred))

Confusion matrix:
[[48 5]
[ 0 90]]
F1 score of the model = 0.972972972973
```

2. Using sklearn library fit a Naïve Bayes classifier on Social_Network_Ads.csv and German_credit_score.csv

Social Network Ads.csv

```
In [13]:

df = pd.read_csv('/content/sample_data/Social_Network_Ads.csv')
    df.head()

Out[13]:
```

```
User ID Gender Age EstimatedSalary Purchased
0 15624510
              Male
                     19
                                  19000
                                                 0
1 15810944
                                  20000
              Male
                                                 0
2 15668575 Female
                                  43000
                                                 0
                     26
3 15603246 Female
                                  57000
                                                 0
4 15804002
              Male
                     19
                                  76000
                                                 0
```

```
In [15]:
```

dtype: int64

```
df.duplicated().sum()
Out[15]:
```

0

In [16]:

```
le = sklearn.preprocessing.LabelEncoder()

df['Gender'] = le.fit_transform(df['Gender'])
    df.head()
```

Out[16]:

```
1 15810944
                 35
                           20000
                                       0
              1
2 15668575
                 26
                           43000
                                       0
3 15603246
                                       0
                 27
                           57000
4 15804002
                           76000
                 19
                                       0
In [17]:
X = df.iloc[:, :-1]
y = df.iloc[:,-1]
df = df.drop("User ID", axis =1)
In [18]:
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 4 columns):
 # Column
                      Non-Null Count Dtype
    -----
                      _____
                      400 non-null
                                     int64
 0
    Gender
 1
                     400 non-null
                                      int64
    EstimatedSalary 400 non-null
                                      int64
 3
                      400 non-null
   Purchased
                                      int64
dtypes: int64(4)
memory usage: 12.6 KB
In [19]:
X train, X test, y train, y test = train test split (X,y, test size = 0.2, random state
= 41)
In [20]:
se = sklearn.preprocessing.StandardScaler()
X train = se.fit transform(X train)
X test = se.fit_transform(X_test)
X train
Out[20]:
array([[-1.53743998, -0.95118973, -0.06599205, 2.21413759],
       [ 1.14481726, -0.95118973, -0.64988486, 0.0381701 ],
       [ 1.07684764, 1.05131497, 0.42058529, -0.1359073 ],
       [-1.15890907, -0.95118973, 1.49105544, 0.35731199],
       [-1.37407341, 1.05131497, -0.74720033,
                                               0.2992862 ],
       [0.17766241, 1.05131497, 1.29642451, -1.3544491]])
In [21]:
gnb = GaussianNB()
gnb.fit(X train, y train)
Out[21]:
GaussianNB()
In [22]:
y pred = gnb.predict(X test)
y trainpred = gnb.predict(X train)
In [23]:
print("Accuracy in train_set= ",accuracy_score(y_train,y_trainpred))
print("Accuracy in test set= ",accuracy score(y test,y pred))
```

0 15624510 Gender Age Estimated Salary Purchased

Accuracy in train cot= 0.88/375

```
print(confusion_matrix(y_test,y_pred))
[[46 4]
 [ 7 23]]
German_credit_score.csv
In [25]:
gc = pd.read csv('/content/sample data/german credit data.csv')
In [26]:
gc.head()
Out[26]:
   Unnamed:
                                                      Checking
                                                                    Credit
                                           Saving
                    Sex Job Housing
                                                                           Duration
                                                                                                     Risk
             Age
                                                                                            Purpose
          0
                                         accounts
                                                       account
                                                                   amount
0
                           2
                                                           little
          0
              67
                   male
                                own
                                             NaN
                                                                      1169
                                                                                 6
                                                                                            radio/TV
                                                                                                    good
1
              22 female
                           2
                                            little
                                                      moderate
                                                                      5951
                                                                                48
                                                                                            radio/TV
          1
                                own
                                                                                                     bad
2
              49
                   male
                                             little
                                                           NaN
                                                                      2096
                                                                                12
                                                                                           education good
                                own
                           2
                                                          little
                                                                                42 furniture/equipment good
3
          3
              45
                                            little
                                                                      7882
                   male
                                free
              53
                   male
                                free
                                             little
                                                           little
                                                                      4870
                                                                                24
                                                                                                      bad
                                                                                                car
In [27]:
gc.isnull().sum()
Out[27]:
Unnamed: 0
                          0
                          0
Age
                          0
Sex
Job
                          0
Housing
                          0
Saving accounts
                       183
                       394
Checking account
Credit amount
                         0
Duration
                          0
                          0
Purpose
                          0
Risk
dtype: int64
In [28]:
gc.shape
Out[28]:
(1000, 11)
In [29]:
gc.duplicated().sum()
Out[29]:
0
In [30]:
gc = gc.drop("Unnamed: 0",axis = 1)
```

Accuracy in test_set= 0.8625

In [24]:

In [31]:

```
gc.drop("Checking account", axis =1)
sav = gc["Saving accounts"].value_counts()
print(sav)
```

little 603 moderate 103 quite rich 63 rich 48

Name: Saving accounts, dtype: int64

In [32]:

```
sav = "little"
gc["Saving accounts"] = gc["Saving accounts"].fillna(sav)
```

In [33]:

```
le = sklearn.preprocessing.LabelEncoder()

gc['Sex']= le.fit_transform(gc['Sex'])
gc['Housing']= le.fit_transform(gc['Housing'])
gc['Saving accounts']= le.fit_transform(gc['Saving accounts'])
gc['Checking account']= le.fit_transform(gc['Checking account'])
gc['Purpose']= le.fit_transform(gc['Purpose'])
gc['Risk']= le.fit_transform(gc['Risk'])
gc.head()
```

Out[33]:

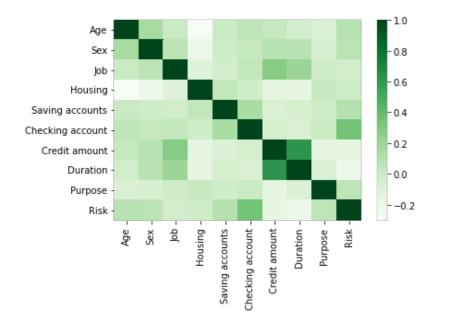
	Age	Sex	Job	Housing	Saving accounts	Checking account	Credit amount	Duration	Purpose	Risk
0	67	1	2	1	0	0	1169	6	5	1
1	22	0	2	1	0	1	5951	48	5	0
2	49	1	1	1	0	3	2096	12	3	1
3	45	1	2	0	0	0	7882	42	4	1
4	53	1	2	0	0	0	4870	24	1	0

In [34]:

```
sns.heatmap(gc.corr(),cmap = 'Greens')
```

Out[34]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f0ceaca2d90>



```
In [35]:
gc.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 10 columns):
 # Column
                      Non-Null Count Dtype
                      _____
   Age
                      1000 non-null
0
                                    int64
1
   Sex
                      1000 non-null
                                      int64
    Job
                      1000 non-null
                                      int64
 3
    Housing
                      1000 non-null
                                      int64
                                    int64
   Saving accounts 1000 non-null
    Checking account 1000 non-null
                                    int64
 5
                                    int64
 6
    Credit amount
                      1000 non-null
7
                      1000 non-null int64
   Duration
8
   Purpose
                      1000 non-null int64
9
                      1000 non-null
   Risk
                                    int64
dtypes: int64(10)
memory usage: 78.2 KB
In [36]:
X = gc.iloc[:, :-1]
y = gc.iloc[:,-1]
In [37]:
X_train, X_test, y_train, y_test = train_test_split (X,y, test_size = 0.2, random_state
= 41)
In [38]:
se = sklearn.preprocessing.StandardScaler()
X train = se.fit transform(X train)
X test = se.fit transform(X test)
X train
Out[38]:
array([[ 2.56212222, -1.52299116,
                                  0.14200319, ..., -0.88762883,
        -1.25200183, 1.07086157],
       [ 0.68347115, 0.65660263, 0.14200319, ..., 0.55321125,
       -0.74210799, -0.95082399],
       [-1.2846395, -1.52299116, 0.14200319, ..., -0.8407751,
       -0.74210799, 1.07086157],
       [ 0.95184988, -1.52299116, -1.41419617, ..., 0.11320899,
       -0.48716107, -0.95082399],
       [-1.19517992, -1.52299116, 0.14200319, ..., -0.56458473,
       -0.99705491, 1.07086157],
       [-0.47950332, 0.65660263, 0.14200319, ..., -0.53992488,
       -1.25200183, 1.07086157]])
In [39]:
gnb = GaussianNB()
gnb.fit(X_train, y_train)
Out[39]:
GaussianNB()
In [40]:
y pred = gnb.predict(X test)
y trainpred = gnb.predict(X train)
In [41]:
```

print("Accuracy in train set= ".accuracy score(v train.v trainpred))

```
print("Accuracy in test_set= ",accuracy_score(y_test,y_pred))

Accuracy in train_set= 0.7325
Accuracy in test_set= 0.72

In [42]:

print(confusion_matrix(y_test,y_pred))

[[ 27  42]
  [ 14  117]]
```