MACHINE LEARNING ASSIGNMENT-4

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Video link:

https://drive.google.com/file/d/16LHd6uEwrf1DfZA7Kdky79AxJRWvQMlJ/view?usp=share_link

Github link:

https://github.com/Sonalika2229/ML_Assignment4

1.Pandas:

```
import warnings
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn import preprocessing
import matplotlib.pyplot as plt
from scipy.stats.stats import pearsonr
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, recall_score, precision_score, classification_report, confusion_matrix
warnings.filterwarnings("ignore")
```

Importing all the required libraries.

	Duration	Pulse	Maxpulse	Calories
0	60	110	130	409.1
1	60	117	145	479.0
2	60	103	135	340.0
3	45	109	175	282.4
4	45	117	148	406.0

The Pandas library provides the pd.read_csv() function, which reads a CSV file and builds a DataFrame object from it.

df.describe()

 \Box

	Duration	Pulse	Maxpulse	Calories
count	169.000000	169.000000	169.000000	164.000000
mean	63.846154	107.461538	134.047337	375.790244
std	42.299949	14.510259	16.450434	266.379919
min	15.000000	80.000000	100.000000	50.300000
25%	45.000000	100.000000	124.000000	250.925000
50%	60.000000	105.000000	131.000000	318.600000
75%	60.000000	111.000000	141.000000	387.600000
max	300.000000	159.000000	184.000000	1860.400000

The df.describe() method in Pandas is a built-in function that creates descriptive statistics for the DataFrame df.

```
df.isnull().any()#Checking if the data has null values.
     Duration
                  False
 \Box
     Pulse
                  False
     Maxpulse
                False
     Calories
                  True
     dtype: bool
[163] #Replace the null values with the mean
     df.fillna(df.mean(), inplace=True)
     df.isnull().any()
     Duration
                  False
     Pulse
                 False
     Maxpulse
                False
     Calories
                False
     dtype: bool
```

The df.fillna() method uses the mean value of each column to fill in any missing values in the DataFrame df.

The df.isnull().any() is used to check if there are any missing values remaining in the DataFrame.

```
#Select at least two columns and aggregate the data using: min, max, count, mean.

df.agg({'Maxpulse':['min','max','count','mean'],'Calories':['min','max','count','mean']})

Maxpulse Calories

min 100.000000 50.300000

max 184.000000 1860.400000

count 169.000000 169.000000

mean 134.047337 375.790244
```

The agg() method is used to do the aggregate computations of the Maxpulse and Calories on the dataframe df.

```
#Filtering the dataframe to select the rows with calories values between 500 and 1000.

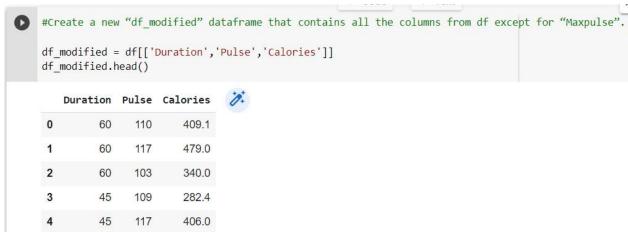
df.loc[(df['Calories']>500)&(df['Calories']<1000)]
```

The df.loc() function is used to select the rows with calories values between 500 and 1000

```
#Filter the dataframe to select the rows with calories values > 500 and pulse < 100.

df.loc[(df['Calories']>500)&(df['Pulse']<100)]
```

The df.loc() function is used to select the rows with calories values that are greater than 500 and the pulse value less than 100.



New DataFrame df_modified is created that includes only Duration, Pulse, and Calories columns of the original DataFrame df.

```
#Delete the "Maxpulse" column from the main df dataframe

del df['Maxpulse']
```

The Maxpulse column is removed from the dataframe df using del df['MaxPulse']

```
[170] df.dtypes

Duration int64
Pulse int64
Calories float64
dtype: object
```

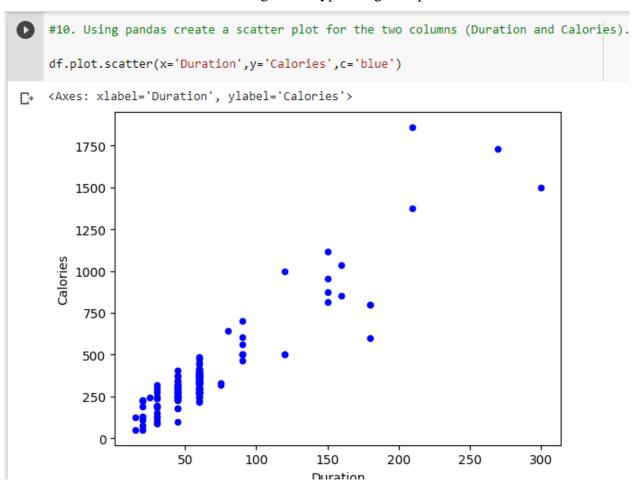
The df.dtypes is used to display the data types of each column in the DataFrame.

```
#Convert the datatype of Calories column to int datatype.

df['Calories'] = df['Calories'].astype(np.int64)
df.dtypes

Duration int64
Pulse int64
Calories int64
dtype: object
```

The astype() method is used to cast a column of a DataFrame to a specific data type. Here the Calories column is cast to the 64-bit integer data type using the np.int64.

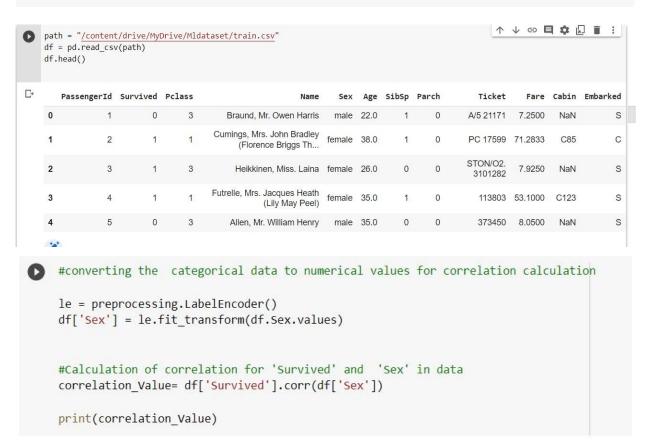


The scattered plot of the Duration and Calories columns in the DataFrame df is displayed.

Question: 2 Titanic Dataset

- 1. Find the correlation between 'survived' (target column) and 'sex' column for the Titanic use case inclass. a. Do you think we should keep this feature?
- 2. Do at least two visualizations to describe or show correlations.
- 3. Implement Naïve Bayes method using scikit-learn library and report the accuracy.

```
[173] path = "/content/drive/MyDrive/Mldataset/train.csv"
    df = pd.read_csv(path)
    df.head()
```



r→ -0.5433513806577555

Yes, we should keep the 'Survived' and 'Sex' features helps classify the data accurately

matrix = df.corr() #printing the correlation matrix
print(matrix)

	PassengerId	Survived	Pclass	Sex	Age	SibSp	1
PassengerId	1.000000	-0.005007	-0.035144	0.042939	0.036847	-0.057527	
Survived	-0.005007	1.000000	-0.338481	-0.543351	-0.077221	-0.035322	
Pclass	-0.035144	-0.338481	1.000000	0.131900	-0.369226	0.083081	
Sex	0.042939	-0.543351	0.131900	1.000000	0.093254	-0.114631	
Age	0.036847	-0.077221	-0.369226	0.093254	1.000000	-0.308247	
SibSp	-0.057527	-0.035322	0.083081	-0.114631	-0.308247	1.000000	
Parch	-0.001652	0.081629	0.018443	-0.245489	-0.189119	0.414838	
Fare	0.012658	0.257307	-0.549500	-0.182333	0.096067	0.159651	
	Survived Pclass Sex Age SibSp Parch	PassengerId 1.000000 Survived -0.005007 Pclass -0.035144 Sex 0.042939 Age 0.036847 SibSp -0.057527 Parch -0.001652	PassengerId 1.000000 -0.005007 Survived -0.005007 1.000000 Pclass -0.035144 -0.338481 Sex 0.042939 -0.543351 Age 0.036847 -0.077221 SibSp -0.057527 -0.035322 Parch -0.001652 0.081629	PassengerId 1.000000 -0.005007 -0.035144 Survived -0.005007 1.000000 -0.338481 Pclass -0.035144 -0.338481 1.000000 Sex 0.042939 -0.543351 0.131900 Age 0.036847 -0.077221 -0.369226 SibSp -0.057527 -0.035322 0.083081 Parch -0.001652 0.081629 0.018443	PassengerId 1.000000 -0.005007 -0.035144 0.042939 Survived -0.005007 1.000000 -0.338481 -0.543351 Pclass -0.035144 -0.338481 1.000000 0.131900 Sex 0.042939 -0.543351 0.131900 1.000000 Age 0.036847 -0.077221 -0.369226 0.093254 SibSp -0.057527 -0.035322 0.083081 -0.114631 Parch -0.001652 0.081629 0.018443 -0.245489	PassengerId 1.000000 -0.005007 -0.035144 0.042939 0.036847 Survived -0.005007 1.000000 -0.338481 -0.543351 -0.077221 Pclass -0.035144 -0.338481 1.000000 0.131900 -0.369226 Sex 0.042939 -0.543351 0.131900 1.000000 0.093254 Age 0.036847 -0.077221 -0.369226 0.093254 1.000000 SibSp -0.057527 -0.035322 0.083081 -0.114631 -0.308247 Parch -0.001652 0.081629 0.018443 -0.245489 -0.189119	PassengerId 1.000000 -0.005007 -0.035144 0.042939 0.036847 -0.057527 Survived -0.005007 1.000000 -0.338481 -0.543351 -0.077221 -0.035322 Pclass -0.035144 -0.338481 1.000000 0.131900 -0.369226 0.083081 Sex 0.042939 -0.543351 0.131900 1.000000 0.093254 -0.114631 Age 0.036847 -0.077221 -0.369226 0.093254 1.000000 -0.308247 SibSp -0.057527 -0.035322 0.083081 -0.114631 -0.308247 1.000000 Parch -0.001652 0.081629 0.018443 -0.245489 -0.189119 0.414838

 Parch
 Fare

 PassengerId
 -0.001652
 0.012658

 Survived
 0.081629
 0.257307

 Pclass
 0.018443
 -0.549500

 Sex
 -0.245489
 -0.182333

 Age
 -0.189119
 0.096067

 SibSp
 0.414838
 0.159651

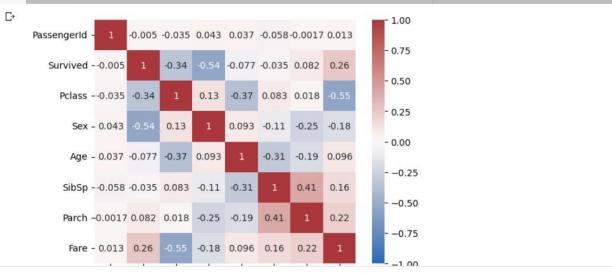
 Parch
 1.000000
 0.216225

 Fare
 0.216225
 1.000000

One way of visualizing the correlation matrix in form of the spread chart df.corr().style.background_gradient(cmap="Reds")

\Box		PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
	Passengerld	1.000000	-0.005007	-0.035144	0.042939	0.036847	-0.057527	-0.001652	0.012658
	Survived	-0.005007	1.000000	-0.338481	-0.543351	-0.077221	-0.035322	0.081629	0.257307
	Pclass	-0.035144	-0.338481	1.000000	0.131900	-0.369226	0.083081	0.018443	-0.549500
	Sex	0.042939	-0.543351	0.131900	1.000000	0.093254	-0.114631	-0.245489	-0.182333
	Age	0.036847	-0.077221	-0.369226	0.093254	1.000000	-0.308247	-0.189119	0.096067
	SibSp	-0.057527	-0.035322	0.083081	-0.114631	-0.308247	1.000000	0.414838	0.159651
	Parch	-0.001652	0.081629	0.018443	-0.245489	-0.189119	0.414838	1.000000	0.216225
	Fare	0.012658	0.257307	-0.549500	-0.182333	0.096067	0.159651	0.216225	1.000000

sns.heatmap(matrix, annot=True, vmax=1, vmin=-1, center=0, cmap='vlag') #Second form of visualizing correlation matriX
plt.show()



```
#Loaded the data files test and train and merged files
      trainraw = pd.read_csv('/content/drive/MyDrive/Mldataset/train.csv')
      testraw = pd.read_csv('/content/drive/MyDrive/Mldataset/test.csv')
      trainraw['train'] = 1
      testraw['train'] = 0
      df = trainraw.append(testraw, sort=False)
      features = ['Age', 'Embarked', 'Fare', 'Parch', 'Pclass', 'Sex', 'SibSp']
      target = 'Survived'
      df = df[features + [target] + ['train']]
      df['Sex'] = df['Sex'].replace(["female", "male"], [0, 1])
      df['Embarked'] = df['Embarked'].replace(['5', 'C', 'Q'], [1, 2, 3])
      train = df.query('train == 1')
      test = df.query('train == 0')
[179] # Dropping the missing values from the train set.
      train.dropna(axis=0, inplace=True)
      labels = train[target].values
```

train.drop(['train', target, 'Pclass'], axis=1, inplace=True)
test.drop(['train', target, 'Pclass'], axis=1, inplace=True)

GaussianNB()

Summary of the predictions made by the classifier print(classification_report(B_val, A_pred)) print(confusion_matrix(B_val, A_pred)) # Describing the Accuracy score from sklearn.metrics import accuracy_score print('Accuracy is',accuracy_score(B_val, A_pred))

₽		precision	recall	f1-score	support
	0.0	0.79	0.80	0.80	85
	1.0	0.70	0.69	0.70	58
	accuracy			0.76	143
	macro avg	0.75	0.74	0.75	143
	weighted avg	0.75	0.76	0.75	143
	[[68 17] [18 40]]				
	[10 40]]				

Accuracy is 0.7552447552447552

Question-3:

(Glass Dataset)

₽

- 1. Implement Naïve Bayes method using scikit-learn library. a. Use the glass dataset available in Link also provided in your assignment. b. Use train_test_split to create training and testing part.
- 2. Evaluate the model on testing part using score and classification_report(y_true, y_pred)
- 3. Implement linear SVM method using scikit library a. Use the glass dataset available in Link also provided in your assignment. b. Use train_test_split to create training and testing part.
- 4. Evaluate the model on testing part using score and classification_report(y_true, y_pred)

```
[183] path = "_content/drive/MyDrive/Mldataset/glass.csv"
    df = pd.read_csv(path)
    df.head()
```

```
RI Na Mg Al Si K Ca Ba Fe Type 

0 1.52101 13.64 4.49 1.10 71.78 0.06 8.75 0.0 0.0 1

4 1.54764 12.00 2.60 1.26 72.72 0.49 7.92 0.0 0.0 1
```

```
// [183] path = "/content/drive/MyDrive/Mldataset/glass.csv"

df = pd.read_csv(path)

df.head()
```



df.corr().style.background_gradient(cmap="Blues")

	RI	Na	Mg	Al	Si	K	Ca	Ва	Fe	Type
RI	1.000000	-0.191885	-0.122274	-0.407326	-0.542052	-0.289833	0.810403	-0.000386	0.143010	-0.164237
Na	-0.191885	1.000000	-0.273732	0.156794	-0.069809	-0.266087	-0.275442	0.326603	-0.241346	0.502898
Mg	-0.122274	-0.273732	1.000000	-0.481799	-0.165927	0.005396	-0.443750	-0.492262	0.083060	-0.744993
AI	-0.407326	0.156794	-0.481799	1.000000	-0.005524	0.325958	-0.259592	0.479404	-0.074402	0.598829
Si	-0.542052	-0.069809	-0.165927	-0.005524	1.000000	-0.193331	-0.208732	-0.102151	-0.094201	0.151565
K	-0.289833	-0.266087	0.005396	0.325958	-0.193331	1.000000	-0.317836	-0.042618	-0.007719	-0.010054
Ca	0.810403	-0.275442	-0.443750	-0.259592	-0.208732	-0.317836	1.000000	-0.112841	0.124968	0.000952
Ва	-0.000386	0.326603	-0.492262	0.479404	-0.102151	-0.042618	-0.112841	1.000000	-0.058692	0.575161
Fe	0.143010	-0.241346	0.083060	-0.074402	-0.094201	-0.007719	0.124968	-0.058692	1.000000	-0.188278
Туре	-0.164237	0.502898	-0.744993	0.598829	0.151565	-0.010054	0.000952	0.575161	-0.188278	1.000000

```
sns.heatmap(matrix, annot=True, vmax=1, vmin=-1, center=0, cmap='vlag')
     plt.show()
\Box
                                                                                         1.00
                             -0.005 -0.035 0.043 0.037 -0.058-0.0017 0.013
       PassengerId
                                                                                        - 0.75
          Survived -- 0.005
                                                   -0.077 -0.035 0.082
                                     -0.34
                                                                           0.26
                                                                                        - 0.50
             Pclass -- 0.035 -0.34
                                             0.13
                                                    -0.37
                                                           0.083 0.018
                                                                                        -0.25
                                                    0.093 -0.11
                Sex - 0.043
                                     0.13
                                                                   -0.25
                                                                          -0.18
                                                                                        - 0.00
               Age - 0.037 -0.077 -0.37
                                            0.093
                                                            -0.31 -0.19
                                                                          0.096
                                                                                        - -0.25
              SibSp --0.058 -0.035 0.083 -0.11
                                                    -0.31
                                                                    0.41
                                                                           0.16
                                                                                        -0.50
              Parch -0.0017 0.082 0.018 -0.25
                                                    -0.19
                                                            0.41
                                                                           0.22
                                                                                         -0.75
               Fare - 0.013
                                      0.55
                                             -0.18 0.096
                              0.26
                                                            0.16
                                                                    0.22
                                                                             1
                                                                                          -1.00
                                                                         completed at 7:21 PM
                                                                   Ns
/[186] features = ['Rl', 'Na', 'Mg', 'Al', 'Si', 'K', 'Ca', 'Ba', 'Fe']
      target = 'Type'
      A_train, A_val, B_train, B_val = train_test_split(df[::-1], df['Type'],test_size=0.2, random_state=1)
      classifier = GaussianNB()
      classifier.fit(A_train, B_train)
      y_pred = classifier.predict(A_val)
      # Summary of the predictions made by the classifier
      print(classification_report(B_val, y_pred))
      print(confusion_matrix(B_val, y_pred))
```

Accuracy score

print('Accuracy is',accuracy_score(B_val, y_pred))

```
precision recall f1-score support
С⇒
                    0.90
                             0.95
                                     0.92
                                                19
             1
             2
                    0.92
                             0.92
                                     0.92
                                                12
             3
                    1.00
                             0.50
                                     0.67
                                                 6
             5
                    0.00
                             0.00
                                     0.00
                                                 1
                    1.00
                             1.00
                                     1.00
                                                 1
             6
                    0.75
             7
                             0.75
                                     0.75
                                                 4
      accuracy
                                     0.84
                                                43
                    0.76
                             0.69
                                     0.71
                                                43
      macro avg
                                     0.85
   weighted avg
                    0.89
                             0.84
                                                43
   [[18 1 0 0 0 0]
    [111 0 0 0 0]
    [1 0 3 2 0 0]
    [000001]
    [000010]
    [0 0 0 1 0 3]]
   Accuracy is 0.8372093023255814
```

```
[187] from sklearn.svm import SVC, LinearSVC

classifier = LinearSVC()

classifier.fit(A_train, B_train)

y_pred = classifier.predict(A_val)

# Summary of the predictions made by the classifier print(classification_report(B_val, y_pred))
print(confusion_matrix(B_val, y_pred))
# Accuracy score
from sklearn.metrics import accuracy_score
print('accuracy is',accuracy_score(B_val, y_pred))
```

_							
O		pre	ecision	recall	f1-score	support	
₽							
L		1	1.00	0.95	0.97	19	
		2	1.00	0.08	0.15	12	
		3	0.26	1.00	0.41	6	
		5	0.00	0.00	0.00	1	
		5	0.00	0.00	0.00	1	
		7	0.00	0.00	0.00	4	
	accurac	y			0.58	43	
	macro av	g	0.38	0.34	0.26	43	
	weighted av	g	0.76	0.58	0.53	43	
	[[18 0 1	0 0	0]				
	[0 1 10	1 0	0]				
	[006	0 0	0]				
	[001	0 0	0]				
	[001	0 0	0]				
	[004	0 0	0]]				
	accuracy is	0.583	139534883	72093			

The accuracy for Naïve Bayes method is 0.8372093023255814. Finally, because of the amount of data Naïve Bayes algorithm gives better accuracy compared to Linear SVM.