Assignment-4

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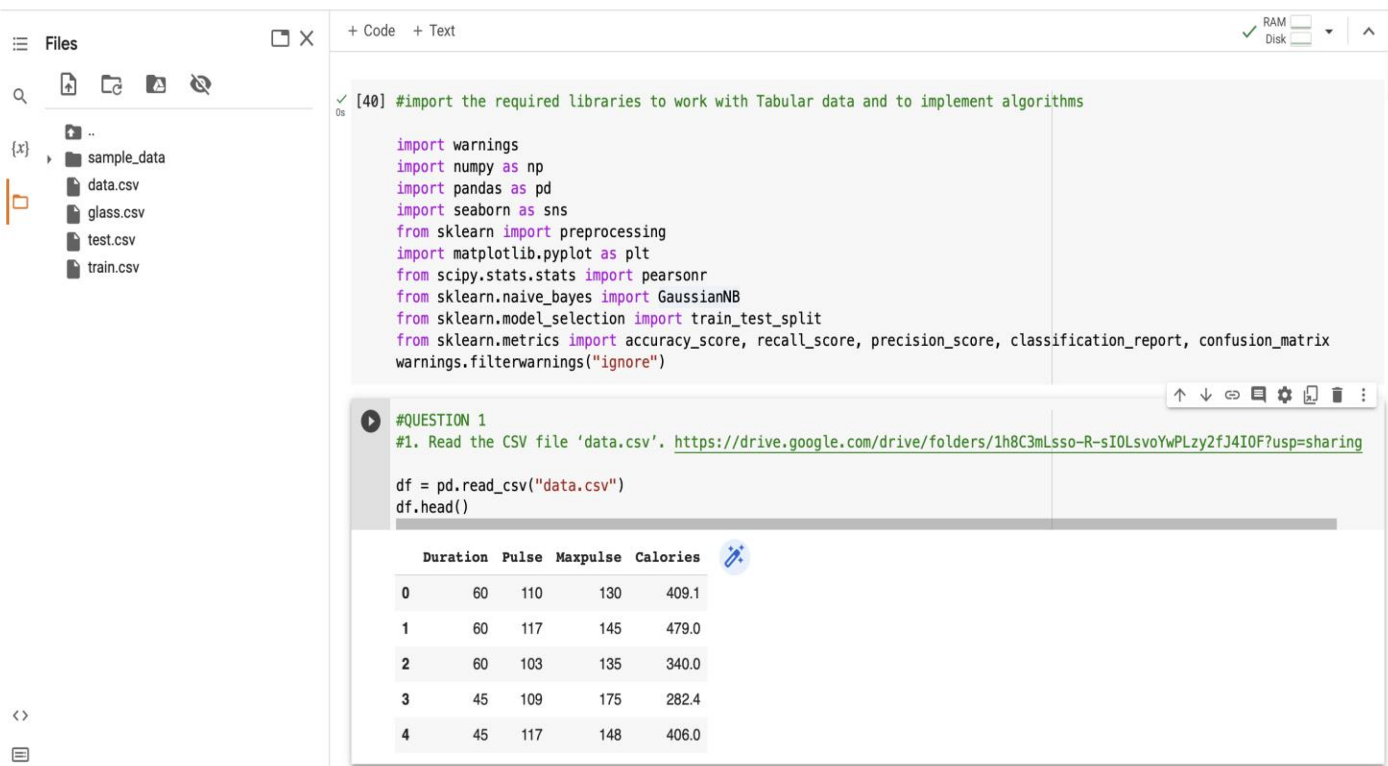
Github Link:

https://github.com/singammanasvi9440/Assignment-4

1. Pandas

1.



Read the CSV file 'data.csv'.

2.

```python
#2. Show the basic statistical description about the data.

df.describe()
```

	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

Show the basic statistical description about the data using describe ().

3,4.

```python
#3. Check if the data has null values.

df.isnull().any()
```

```
Duration     False
Pulse        False
Maxpulse     False
Calories      True
dtype: bool
```

```python
#3a.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
```

```python
#4. 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

Check if the data has null values using isnull().

Replace the null values with the df.mean().

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

5.

```
#5. Filter the dataframe to select the rows with calories values between 500 and 1000.
df.loc[(df['Calories']>500)&(df['Calories']<1000)]
```

	Duration	Pulse	Maxpulse	Calories
51	80	123	146	643.1
62	160	109	135	853.0
65	180	90	130	800.4
66	150	105	135	873.4
67	150	107	130	816.0
72	90	100	127	700.0
73	150	97	127	953.2
75	90	98	125	563.2
78	120	100	130	500.4
90	180	101	127	600.1
99	90	93	124	604.1
103	90	90	100	500.4
106	180	90	120	800.3
108	90	90	120	500.3

Filter the data frame as per the requirements.

6,7.

```
#6. Filter the dataframe to select the rows with calories values > 500 and pulse < 100.
df.loc[(df['Calories']>500)&(df['Pulse']<100)]
```

	Duration	Pulse	Maxpulse	Calories
65	180	90	130	800.4
70	150	97	129	1115.0
73	150	97	127	953.2
75	90	98	125	563.2
99	90	93	124	604.1
103	90	90	100	500.4
106	180	90	120	800.3
108	90	90	120	500.3

```
#7. Create a new “df_modified” dataframe that contains all the columns from df except for “Maxpulse”.
df_modified = df[['Duration','Pulse','Calories']]
df_modified.head()
```

	Duration	Pulse	Calories
0	60	110	409.1
1	60	117	479.0
2	60	103	340.0
3	45	109	282.4
4	45	117	406.0

Filter the data frame and create a new modified data frame.

8,9.

```
[11] #8. Delete the “Maxpulse” column from the main df dataframe

     del df['Maxpulse']
```

```
df.head()
```

	Duration	Pulse	Calories
0	60	110	409.1
1	60	117	479.0
2	60	103	340.0
3	45	109	282.4
4	45	117	406.0

```
[13] df.dtypes

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

```
#9. 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
```

Delete the maxpulse using del

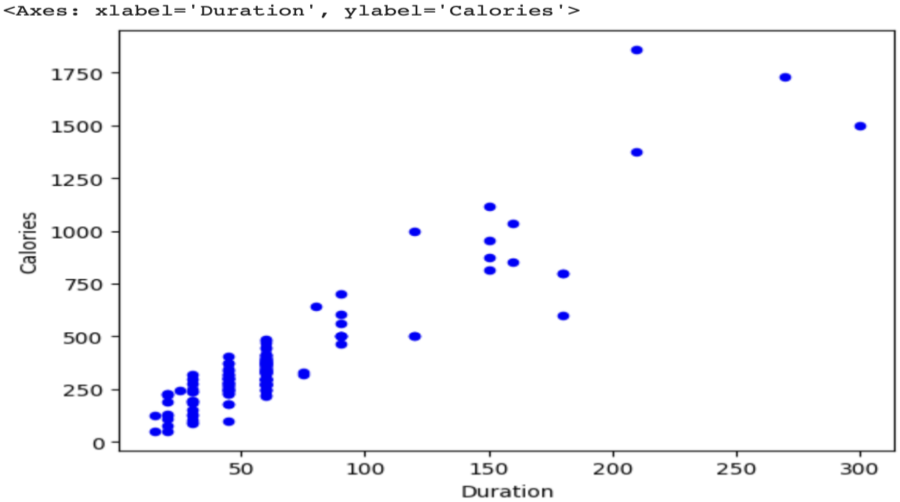
Convert the datatype of calories column into int datatype.

10.

```
#10. Using pandas create a scatter plot for the two columns (Duration and Calories).

df.plot.scatter(x='Duration',y='Calories',c='blue')
```

```
<Axes: xlabel='Duration', ylabel='Calories'>
```



Scatter plot for duration and Calories.

1. Titanic Dataset

1.

```
#1.TITANIC DATASET
Loading the data file into te program
df=pd.read_csv("train.csv")

df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

```
#converted categorical data to numerical values for correlation calculation

label_encoder = preprocessing.LabelEncoder()
df['Sex'] = label_encoder.fit_transform(df.Sex.values)


#Calculation of correlation for 'Survived' and  'Sex' in data
correlation_Value= df['Survived'].corr(df['Sex'])

print(correlation_Value)
```

```
-0.5433513806577555
```

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

Finding correlation between ‘survived’ (target column) and ‘sex’ column.

```
#print correlation matrix
matrix = df.corr()
print(matrix)
```

```
             PassengerId  Survived    Pclass       Sex       Age     SibSp  \
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

                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
```

2.

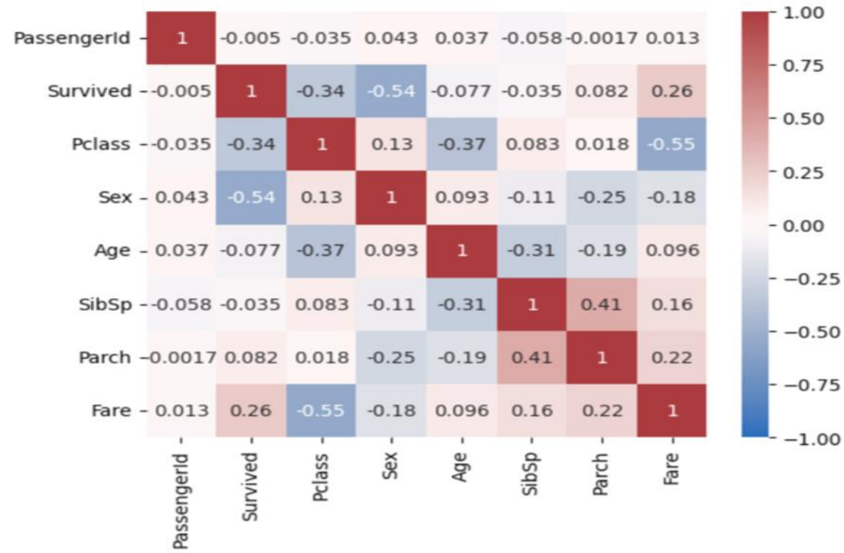
```
# One way of visualizing correlation matrix in form of spread chart

df.corr().style.background_gradient(cmap="Reds")
```

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
PassengerId	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

```
#Second form of visuaizing correlation matriX using heatmap() from seaborn

sns.heatmap(matrix, annot=True, vmax=1, vmin=-1, center=0, cmap='vlag')
plt.show()
```



Two visualizations to show correlations.

3.

```
#Loaded data files test and train and merged files

train_raw = pd.read_csv('train.csv')
test_raw = pd.read_csv('test.csv')
train_raw['train'] = 1
test_raw['train'] = 0
df = train_raw.append(test_raw, 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(['S', 'C', 'Q'], [1, 2, 3])
train = df.query('train == 1')
test = df.query('train == 0')
```

```
# Drop 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)
```

```
#Test and train split

X_train, X_val, Y_train, Y_val = train_test_split(train, labels, test_size=0.2, random_state=1)
```

```
classifier = GaussianNB()

classifier.fit(X_train, Y_train)
```

```
▾ GaussianNB
GaussianNB()
```

```
y_pred = classifier.predict(X_val)

# Summary of the predictions made by the classifier
print(classification_report(Y_val, y_pred))
print(confusion_matrix(Y_val, y_pred))
# Accuracy score
from sklearn.metrics import accuracy_score
print('accuracy is',accuracy_score(Y_val, y_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]]
accuracy is 0.7552447552447552
```

Implementing Naïve Bayes method using scikit-learn library and calculate the accuracy.

2.GLASS DATASET

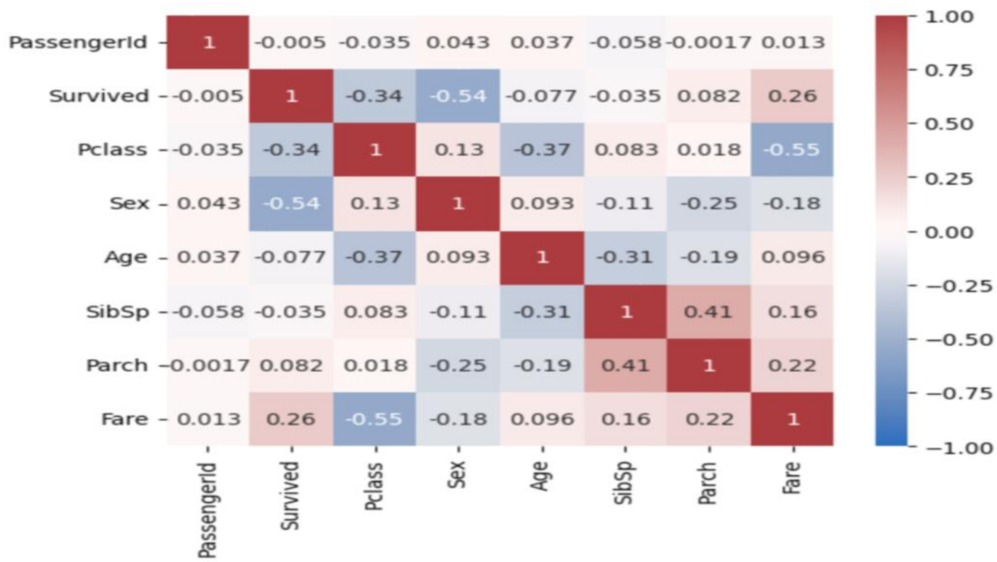
```
glass=pd.read_csv("glass.csv")
glass.head()
```

	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
1	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.0	0.0	1
2	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.0	0.0	1
3	1.51766	13.21	3.69	1.29	72.61	0.57	8.22	0.0	0.0	1
4	1.51742	13.27	3.62	1.24	73.08	0.55	8.07	0.0	0.0	1

```
glass.corr().style.background_gradient(cmap="Reds")
```

	RI	Na	Mg	Al	Si	K	Ca	Ba	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
Al	-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
Ba	-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
Type	-0.164237	0.502898	-0.744993	0.598829	0.151565	-0.010054	0.000952	0.575161	-0.188278	1.000000

```python
sns.heatmap(matrix, annot=True, vmax=1, vmin=-1, center=0, cmap='vlag')
plt.show()
```




```python
X_train, X_val, Y_train, Y_val = train_test_split(glass[::-1], glass['Type'],test_size=0.2, random_state=1)

classifier = GaussianNB()

classifier.fit(X_train, Y_train)


y_pred = classifier.predict(X_val)

# Summary of the predictions made by the classifier
print(classification_report(Y_val, y_pred))
print(confusion_matrix(Y_val, y_pred))
# Accuracy score

print('accuracy is',accuracy_score(Y_val, y_pred))
```

```
              precision    recall  f1-score   support

           1       0.90      0.95      0.92        19
           2       0.92      0.92      0.92        12
           3       1.00      0.50      0.67         6
           5       0.00      0.00      0.00         1
           6       1.00      1.00      1.00         1
           7       0.75      0.75      0.75         4

    accuracy                           0.84        43
   macro avg       0.76      0.69      0.71        43
weighted avg       0.89      0.84      0.85        43

[[18  1  0  0  0  0]
 [ 1 11  0  0  0  0]
 [ 1  0  3  2  0  0]
 [ 0  0  0  0  0  1]
 [ 0  0  0  0  1  0]
 [ 0  0  0  1  0  3]]
accuracy is 0.8372093023255814
```

```python
from sklearn.svm import SVC, LinearSVC

classifier = LinearSVC()

classifier.fit(X_train, Y_train)


y_pred = classifier.predict(X_val)

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

```
              precision    recall  f1-score   support

           1       1.00      0.95      0.97        19
           2       0.57      1.00      0.73        12
           3       0.00      0.00      0.00         6
           5       0.00      0.00      0.00         1
           6       0.00      0.00      0.00         1
           7       0.75      0.75      0.75         4

    accuracy                           0.77        43
   macro avg       0.39      0.45      0.41        43
weighted avg       0.67      0.77      0.70        43

[[18  1  0  0  0  0]
 [ 0 12  0  0  0  0]
 [ 0  5  0  0  0  1]
 [ 0  1  0  0  0  0]
 [ 0  1  0  0  0  0]
 [ 0  1  0  0  0  3]]
accuracy is 0.7674418604651163
```

We got better accuracy for Naïve Bayes method which is 0.8372093023255814. Naive Bayes analysis works well with probabilistic concepts whereas Linear SVM works better with linear regression logics. But to perform more accurately SVM requires large amounts of data to train and test the data. So, due to the amount of data Naive Bayes algorithm gives better accuracy compared to Linear SVM.