Machine learning

Assignment –4

Deepthi Gudibanda

700732646

1.Pandas

#1.Read the provided CSV file ‘data.csv https://drive.google.com/drive/folders/1h8C3mLsso-R-sIOLsvoYwPLzy2fJ4IOF?usp=sharing

In [7]:
```
import pandas as pd
import numpy as np

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

Out[7]:

	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

2. Show the basic statistical description about the data.

In [8]:
```
data.describe()
```

Out[8]:

	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

3. Check if the data has null values.

In [9]:
```
data.isnull().any()
```

Out[9]:
```
Duration    False
Pulse       False
Maxpulse    False
Calories     True
dtype: bool
```

a. Replace the null values with the mean

In [10]:
```
data.fillna(data.mean(), inplace=True)
data.isnull().any()
```

Out[10]:
```
Duration    False
Pulse       False
Maxpulse    False
Calories    False
dtype: bool
```

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

In [12]:
```
data.agg({'Duration':['min','max','count','mean'],'Pulse':['min','max','count','mean']})
```

Out[12]:

	Duration	Pulse
min	15.000000	80.000000
max	300.000000	159.000000
count	169.000000	169.000000
mean	63.846154	107.461538

5. Filter the dataframe to select the rows with calories values between 500 and 1000.

In [13]:
```
data.loc[(data['Calories']>500)&(data['Calories']<1000)]
```

Out[13]:

	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

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

In [14]:
```
data.loc[(data['Calories']>500)&(data['Pulse']<100)]
```

Out[14]:

	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”

In [15]:
```
df_modified = data[['Duration','Pulse','Calories']]
df_modified.head()
```

Out[15]:

	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

8. Delete the “Maxpulse” column from the main df dataframe

In [16]:
```
del data['Maxpulse']
```

In [17]:
```
data.head()
```

Out[17]:

	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

9. Convert the datatype of Calories column to int datatype.

In [18]:
```
data.dtypes
```

Out[18]:
```
Duration       int64
Pulse          int64
Calories     float64
dtype: object
```

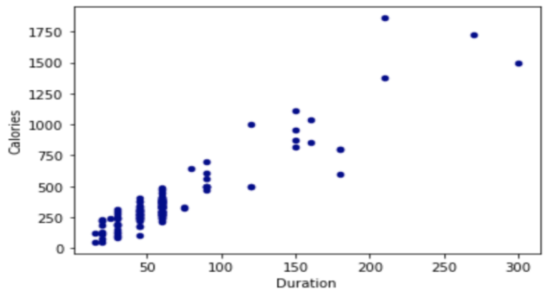
In [19]:
```
data['Calories'] = data['Calories'].astype(np.int64)
data.dtypes
```

Out[19]:
```
Duration    int64
Pulse       int64
Calories    int64
dtype: object
```

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

In [20]:
```
data.plot.scatter(x='Duration',y='Calories',c='DarkBlue')
```

Out[20]: <AxesSubplot:xlabel='Duration', ylabel='Calories'>



1. (Titanic Dataset)

1. Find the correlation between 'survived' (target column) and 'sex' column for the Titanic use case inclass

In [33]:
```
import pandas as pd
import seaborn as sns
from sklearn import preprocessing
import matplotlib.pyplot as plt
```

In [34]:
```
df=pd.read_csv("train.csv")
```

In [35]:
```
df.head()
```

Out[35]:

	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

In [36]:
```
le = preprocessing.LabelEncoder()
df['Sex'] = le.fit_transform(df.Sex.values)
df['Survived'].corr(df['Sex'])
```

Out[36]: -0.543351380657755

a. Do you think we should keep this feature?

A negative (inverse) correlation occurs when the correlation coefficient is less than 0. This is an indication that both variables move in the opposite direction. In short, any reading between 0 and -1 means that the two securities move in opposite directions. If one variable increases, the other variable decreases with the same magnitude (and vice versa). However, the degree to which two securities are negatively correlated might vary over time (and they are almost never exactly correlated all the time). Removing a correlated feature does not make any difference in the outcome of the model. It is always better to remove the highly correlated features first and then least correlated ones.

2. Do at least two visualizations to describe or show correlations.

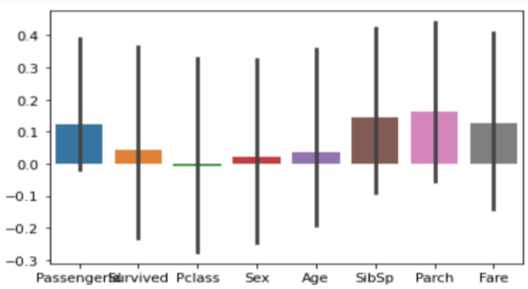
In [37]:
```
des=df.corr()
df.corr().style.background_gradient(cmap="Greens")
```

Out[37]:

	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

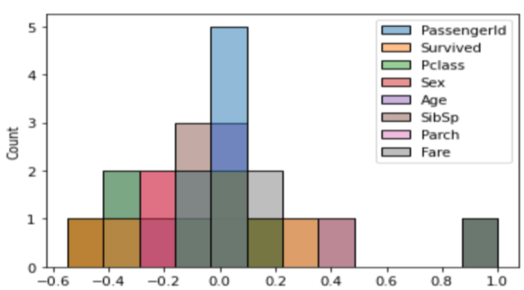
In [38]:
```
sns.barplot(data=des) #BarPlot Visualization for above dataset
```

Out[38]: <AxesSubplot:>



In [39]:
```
sns.histplot(data=des) #Histogram Visualization for above dataset
```

Out[39]: <AxesSubplot:ylabel='Count'>



3. Implement Naïve Bayes method using scikit-learn library and report the accuracy.

In [50]:
```
train_raw = pd.read_csv('train.csv')
test_raw = pd.read_csv('test.csv')

# Join data to analyse and process the set as one.
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']]
# Categorical values need to be transformed into numeric.
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')
```

In [51]:
```
# 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)
```

In [52]:
```
from sklearn.model_selection import train_test_split, cross_validate

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

In [53]:
```
import warnings
import numpy as np
import pandas as pd
import seaborn as sns
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_repor

%matplotlib inline
# Suppress warnings
warnings.filterwarnings("ignore")
```

In [54]:
```
classifier = GaussianNB()

classifier.fit(X_train, Y_train)
```

Out[54]:
```
GaussianNB()
```

In [55]:
```
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
```

2. (Glass Dataset)

1. Implement Naïve Bayes method using scikit-learn library. a. Use the glass dataset available in Link also provided in your assignment.

In [56]:
```
glass=pd.read_csv("glass.csv") #importing glass dataset from given link
```

In [57]:
```
glass.head()
```

Out[57]:

	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

In [58]:
```
des=glass.corr()
glass.corr().style.background_gradient(cmap="Greens")
```

Out[58]:

	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

b. Use train_test_split to create training and testing part

In [59]:
```
features = ['Rl', 'Na', 'Mg', 'Al', 'Si', 'K', 'Ca', 'Ba', 'Fe']
target = 'Type'


X_train, X_val, Y_train, Y_val = train_test_split(glass[::-1], glass[target],test_size=0.2, ran
```

2. Evaluate the model on testing part using score and classification_report(y_true, y_pred)

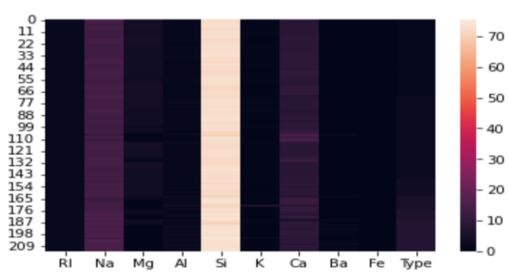
In [60]:
```
classifier = GaussianNB()

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
from sklearn.metrics import accuracy_score
print('\naccuracy 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


[[18  0  0  0  1  0]
 [ 0  0  0  0 12  0]
 [ 0  0  0  0  6  0]
 [ 0  0  0  0  1  0]
 [ 0  0  0  0  1  0]
 [ 0  0  0  0  4  0]]

accuracy is 0.4418604651162791
```

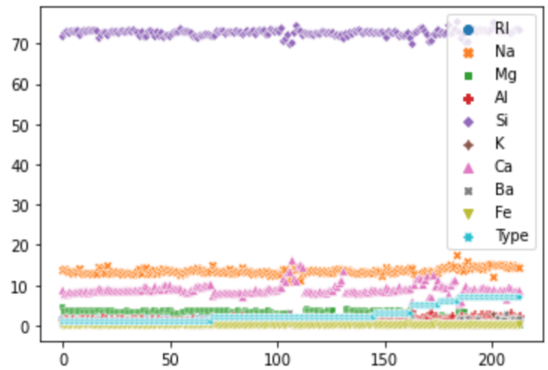
Do at least two visualizations to describe or show correlations in the Glass Dataset.

In [63]:
```
sns.heatmap(data=glass) #HeatMap Visualization for above dataset
```

Out[63]: <AxesSubplot:>



In [64]:
```
sns.scatterplot(data=glass)  #ScatterPlot Visualization for above dataset
```
Out[64]: <AxesSubplot:>



Which algorithm you got better accuracy? Can you justify why?

According to the above accuracy scores Naive Bayes method is best for data visualization than that of Support Vector Machine method. The performance of the each algorithm depends on several factors. So, few algorithms works well for only few of the problems and does not work well for other problems. By evaluating the model using various algorithms we can compare and then state which one is best.

Github link: https://github.com/Deepthi-gudibanda/MachineLearning.git