MACHINE LEARNING ASSIGNMENT 4

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## Q1) Pandas

### 1. Read the provided CSV file 'data.csv'.

```
In [1]: #1.pandas
        import pandas as pd
        #Read the csv file
        data = pd.read_csv("data.csv")
        data.head()
```

Out[1]:

| | 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 [5]: #shows statastical description of data
        data.describe()
```

Out[5]:

| | 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 [6]: #Check if the data has null values
        data.isnull().any()
```

```
Out[6]: Duration    False
        Pulse       False
        Maxpulse    False
        Calories     True
        dtype: bool
```

**a. Replace the null values with the mean**

```
In [7]: #Replace the null values with the mean
        data.fillna(data.mean(), inplace=True)
        data.isnull().any()
```

```
Out[7]: 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 [8]: #Select at least two columns and aggregate the data using: min, max, count, mean
        data.agg({'Maxpulse':['min','max','count','mean'],'Calories':['min','max','count','mean']})
```

Out[8]:

| | Maxpulse | Calories |
|---|---|---|
| min | 100.000000 | 50.300000 |
| max | 184.000000 | 1860.400000 |
| count | 169.000000 | 169.000000 |
| mean | 134.047337 | 375.790244 |

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

```
In [9]: #Filter the dataframe to select the rows with calories values between 500 and 1000.
        data.loc[(data['Calories']>500)&(data['Calories']<1000)]
```

Out[9]:

| | 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 [10]: #Filter the dataframe to select the rows with calories values > 500 and pulse < 100.
         data.loc[(data['Calories']>500)&(data['Pulse']<100)]
```

Out[10]:

| | 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 [11]: #Create a new "df_modified" dataframe that contains all the columns from df except for "Maxpulse"
         df_modified = data[['Duration','Pulse','Calories']]
         df_modified.head()
```

Out[11]:

| | 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 [12]: #Delete the "Maxpulse" column from the main df dataframe
         del data['Maxpulse']
```

```
In [13]: data.head()
```

Out[13]:

| | 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 [14]: data.dtypes
```

```
Out[14]: Duration      int64
         Pulse         int64
         Calories    float64
         dtype: object
```

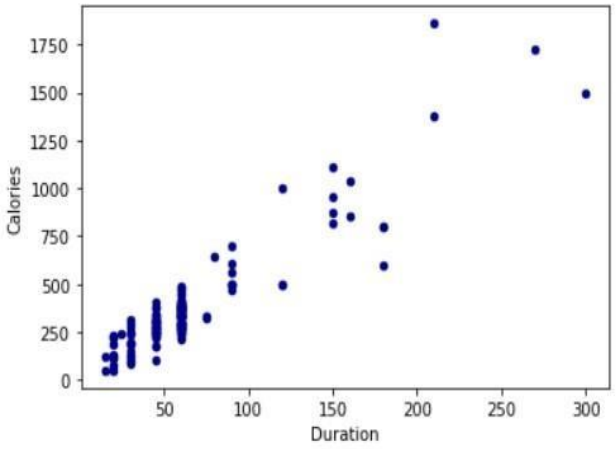
```
In [16]: #Convert the datatype of Calories column to int datatype.
         import numpy as np

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

```
Out[16]: Duration    int64
         Pulse       int64
         Calories    int64
         dtype: object
```

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

```
In [17]: #Using pandas create a scatter plot for the two columns (Duration and Calories).
         data.plot.scatter(x='Duration',y='Calories',c='DarkBlue')
```

```
Out[17]: <Axes: xlabel='Duration', ylabel='Calories'>
```



## 1. (Titanic Dataset) 1. Find the correlation between 'survived' (target column) and 'sex' column for the Titanic use case in class

In [48]:
```
#1.Titanic dataset
import pandas as pd
import seaborn as sns
from sklearn import preprocessing
import matplotlib.pyplot as plt

df=pd.read_csv("train.csv")
df.head()
```

Out[48]:

| | 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 [11]:
```
#correlation between 'survived' (target column) and 'sex' column for the Titanic use case in class.
le = preprocessing.LabelEncoder()
df['Sex'] = le.fit_transform(df.Sex.values)
df['Survived'].corr(df['Sex'])
```

Out[11]: -0.5433513806577547

### a. Do you think we should keep this feature?

**Ans. No, because the accuracy is just 54% only. So we should not keep this feature.**

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

In [56]:
```
# Drop non-numeric columns from the dataframe
df = df.drop(['Name', 'Sex','Ticket','Cabin','Embarked'], axis=1)

#creating corelation matrix
matrix = df.corr()
print(matrix)
```

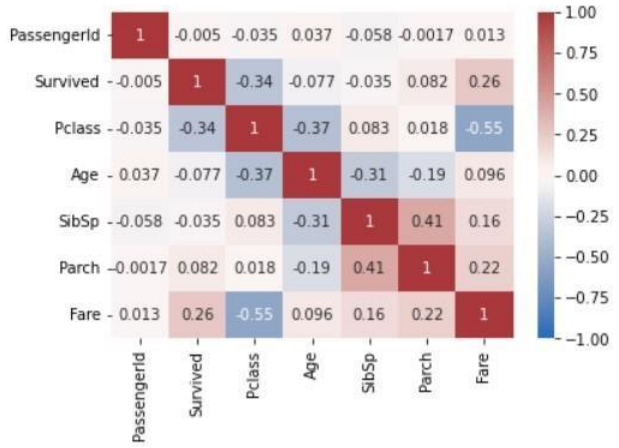
```
             PassengerId  Survived    Pclass       Age     SibSp     Parch  \
PassengerId     1.000000 -0.005007 -0.035144  0.036847 -0.057527 -0.001652
Survived       -0.005007  1.000000 -0.338481 -0.077221 -0.035322  0.081629
Pclass         -0.035144 -0.338481  1.000000 -0.369226  0.083081  0.018443
Age             0.036847 -0.077221 -0.369226  1.000000 -0.308247 -0.189119
SibSp          -0.057527 -0.035322  0.083081 -0.308247  1.000000  0.414838
Parch          -0.001652  0.081629  0.018443 -0.189119  0.414838  1.000000
Fare            0.012658  0.257307 -0.549500  0.096067  0.159651  0.216225

                 Fare
PassengerId  0.012658
Survived     0.257307
Pclass      -0.549500
Age          0.096067
SibSp        0.159651
Parch        0.216225
Fare         1.000000
```

In [57]:
```
#visualization 1 of Titanic Dataset
df.corr().style.background_gradient(cmap="Greens")
```

Out[57]:

| | PassengerId | Survived | Pclass | Age | SibSp | Parch | Fare |
|---|---|---|---|---|---|---|---|
| PassengerId | 1.000000 | -0.005007 | -0.035144 | 0.036847 | -0.057527 | -0.001652 | 0.012658 |
| Survived | -0.005007 | 1.000000 | -0.338481 | -0.077221 | -0.035322 | 0.081629 | 0.257307 |
| Pclass | -0.035144 | -0.338481 | 1.000000 | -0.369226 | 0.083081 | 0.018443 | -0.549500 |
| Age | 0.036847 | -0.077221 | -0.369226 | 1.000000 | -0.308247 | -0.189119 | 0.096067 |
| SibSp | -0.057527 | -0.035322 | 0.083081 | -0.308247 | 1.000000 | 0.414838 | 0.159651 |
| Parch | -0.001652 | 0.081629 | 0.018443 | -0.189119 | 0.414838 | 1.000000 | 0.216225 |
| Fare | 0.012658 | 0.257307 | -0.549500 | 0.096067 | 0.159651 | 0.216225 | 1.000000 |

```
In [52]: #visualization 2 of Titanic Dataset
         sns.heatmap(matrix, annot=True, vmax=1, vmin=-1, center=0, cmap='vlag')
         plt.show()
```




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

```
In [68]: #Naïve Bayes method of Titanic Dataset
import pandas as pd
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.impute import SimpleImputer

# Load the dataset
df = pd.read_csv("train.csv")

# Select features and target
features = ['Age', 'Embarked', 'Fare', 'Parch', 'Pclass', 'Sex', 'SibSp']
target = 'Survived'

# Preprocess categorical variables
df['Sex'] = df['Sex'].replace(["female", "male"], [0, 1])
df['Embarked'] = df['Embarked'].replace(['S', 'C', 'Q'], [1, 2, 3])

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(df[features], df[target], test_size=0.2, random_state=42)

# Impute missing values with the mean
imputer = SimpleImputer(strategy='mean')
X_train_imputed = imputer.fit_transform(X_train)
X_test_imputed = imputer.transform(X_test)

# Train the Naive Bayes model
model = GaussianNB()
model.fit(X_train_imputed, y_train)
```

```
# Make predictions on the test set
y_pred = model.predict(X_test_imputed)

# Calculate the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: {:.2f}%".format(accuracy * 100))
```

```
Accuracy: 77.65%
```

**2. (Glass Dataset)**

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

In [69]:
```
#2.Glass Dataset
glass=pd.read_csv("glass.csv")
glass.head()
```

Out[69]:

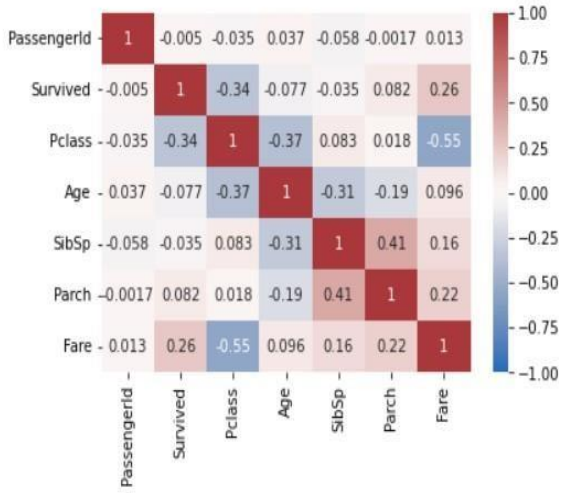
| | RI | Na | Mg | Al | Si | K | Ca | Ba | Fe | Type |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1.52101 | 13.64 | 4.49 | 1.10 | 71.78 | 0.06 | 8.75 | 0.0 | 0.0 | 1 |
| 1 | 1.51761 | 13.89 | 3.60 | 1.36 | 72.73 | 0.48 | 7.83 | 0.0 | 0.0 | 1 |
| 2 | 1.51618 | 13.53 | 3.55 | 1.54 | 72.99 | 0.39 | 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 [70]:
```
#visualization 1 of Glass Dataset
glass.corr().style.background_gradient(cmap="Greens")
```

Out[70]:

| | 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 |

In [71]:
```
#visualization 2 of Glass Dataset
sns.heatmap(matrix, annot=True, vmax=1, vmin=-1, center=0, cmap='vlag')
plt.show()
```




1. **Implement Naïve Bayes method using scikit-learn library.**

   **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)**

In [73]:
```
#Naïve Bayes method of Glass Dataset
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import classification_report

# Load the dataset
glass_data = pd.read_csv('glass.csv')

# Separate the target variable
X = glass_data.drop(['Type'], axis=1)
y = glass_data['Type']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train the Naive Bayes model
model = GaussianNB()
model.fit(X_train, y_train)

# Make predictions on the testing set
y_pred = model.predict(X_test)

# Evaluate the model
score = model.score(X_test, y_test)
report = classification_report(y_test, y_pred)

print("Accuracy Score: {:.2f}%".format(score * 100))
print("\nClassification Report:\n", report)
```

```
Accuracy Score: 55.81%

Classification Report:
              precision    recall  f1-score   support

           1       0.41      0.64      0.50        11
           2       0.43      0.21      0.29        14
           3       0.40      0.67      0.50         3
           5       0.50      0.25      0.33         4
           6       1.00      1.00      1.00         3
           7       0.89      1.00      0.94         8

    accuracy                           0.56        43
   macro avg       0.60      0.63      0.59        43
weighted avg       0.55      0.56      0.53        43
```

**1. Implement linear SVM method using scikit library**

**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)**

In [76]:
```
#Linear SVM method of Glass Dataset
import warnings
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import LinearSVC
from sklearn.metrics import classification_report
#To avoid warnings
warnings.filterwarnings("ignore")

# Load the dataset
glass_data = pd.read_csv('glass.csv')

# Separate the target variable
X = glass_data.drop(['Type'], axis=1)
y = glass_data['Type']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train the Linear SVM model
model = LinearSVC(random_state=42)
model.fit(X_train, y_train)

# Make predictions on the testing set
y_pred = model.predict(X_test)

# Evaluate the model
score = model.score(X_test, y_test)
report = classification_report(y_test, y_pred)

print("Accuracy Score: {:.2f}%".format(score * 100))
print("\nClassification Report:\n", report)
```

```
Accuracy Score: 51.16%

Classification Report:
              precision    recall  f1-score   support

           1       0.37      1.00      0.54        11
           2       0.00      0.00      0.00        14
           3       0.00      0.00      0.00         3
           5       1.00      0.75      0.86         4
           6       0.00      0.00      0.00         3
           7       0.80      1.00      0.89         8

    accuracy                           0.51        43
   macro avg       0.36      0.46      0.38        43
weighted avg       0.34      0.51      0.38        43
```

**Github Link:** https://github.com/ChetanNaga/Machine-Learning

**3. Which algorithm you got better accuracy? Can you justify why?**

**Ans. Naïve Bayes algorithm got better accuracy than Linear SVM algorithm because naïve bayes need small amount of training data Where as Linear SVM need large amount of training data and SVM is more expensive than Naïve bayes algorithm. But it will give output easily.And naïve bayes is good for spam detection and text classification problems**

**So Naïve bayes is better than Linear Svm.**