Summer 2023: ML 5710

(Assignment 2)

GitHub Link: https://github.com/arunkumar2601/Assignment2.git

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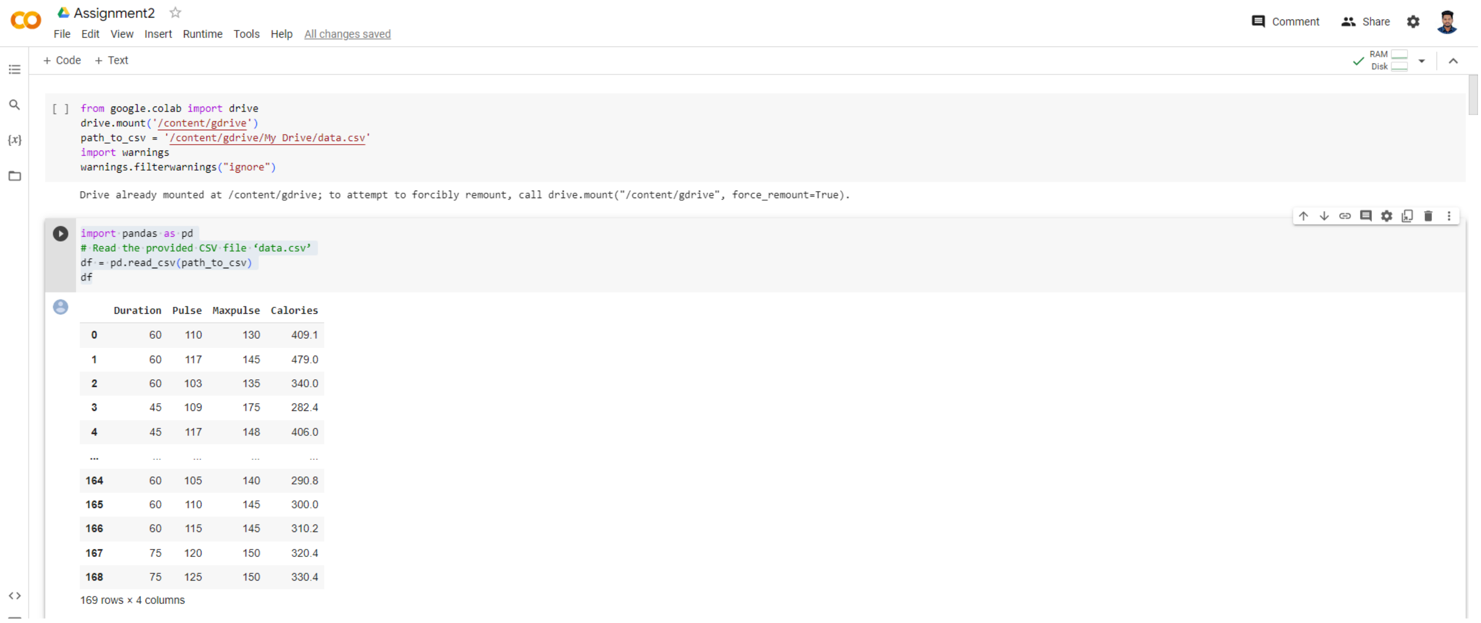
Programming elements:

Classification

A.Pandas

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



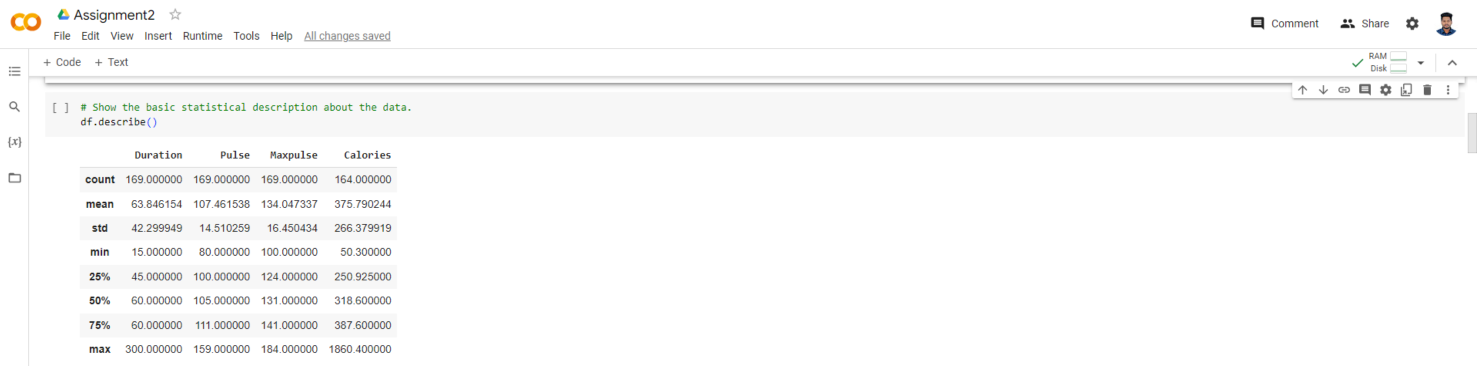
```
from google.colab import drive
drive.mount('/content/gdrive')
path_to_csv = '/content/gdrive/My Drive/data.csv'
import warnings
warnings.filterwarnings("ignore")
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mount("/content/gdrive", force_remount=True).
```

```
import pandas as pd
# Read the provided CSV file ‘data.csv’
df = pd.read_csv(path_to_csv)
df
```

```
     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
...       ...    ...       ...       ...
164        60    105       140     290.8
165        60    110       145     300.0
166        60    115       145     310.2
167        75    120       150     320.4
168        75    125       150     330.4
169 rows × 4 columns
```

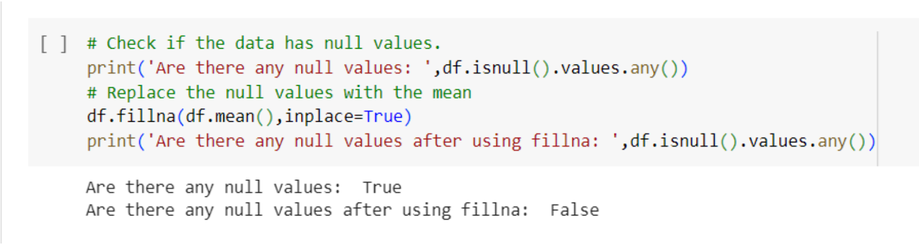
2. Show the basic statistical description about the data.



```
# 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
```

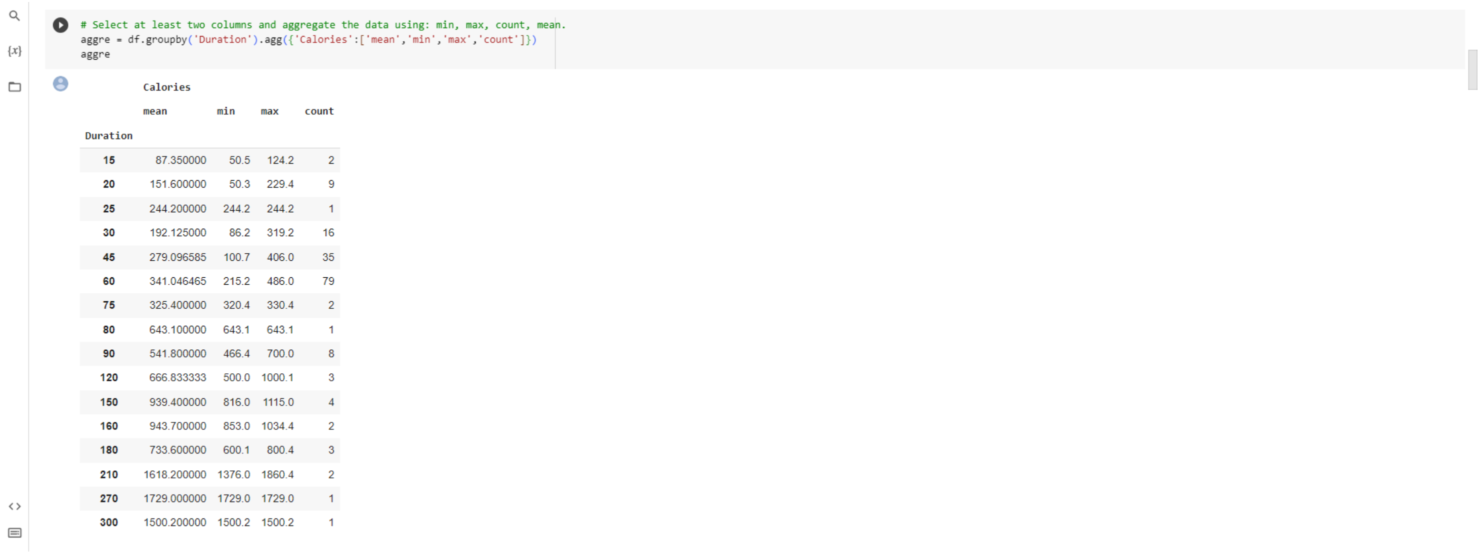
3. Check if the data has null values. **a**. Replace the null values with the mean.



```
[ ]  # Check if the data has null values.
     print('Are there any null values: ',df.isnull().values.any())
     # Replace the null values with the mean
     df.fillna(df.mean(),inplace=True)
     print('Are there any null values after using fillna: ',df.isnull().values.any())
```

```
Are there any null values:  True
Are there any null values after using fillna:  False
```

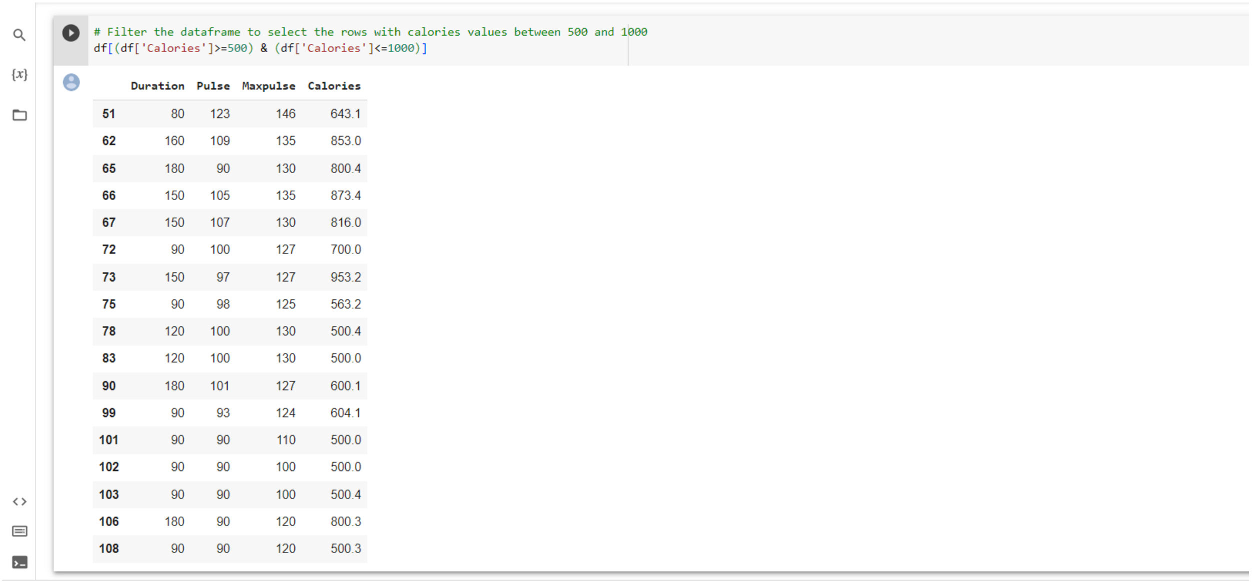
4. Select at least two columns and aggregate the data using: min, max, count, mean.



```
# Select at least two columns and aggregate the data using: min, max, count, mean.
aggre = df.groupby('Duration').agg({'Calories':['mean','min','max','count']})
aggre
```

	Calories			
	mean	min	max	count
Duration				
15	87.350000	50.5	124.2	2
20	151.600000	50.3	229.4	9
25	244.200000	244.2	244.2	1
30	192.125000	86.2	319.2	16
45	279.096585	100.7	406.0	35
60	341.046465	215.2	486.0	79
75	325.400000	320.4	330.4	2
80	643.100000	643.1	643.1	1
90	541.800000	466.4	700.0	8
120	666.833333	500.0	1000.1	3
150	939.400000	816.0	1115.0	4
160	943.700000	853.0	1034.4	2
180	733.600000	600.1	800.4	3
210	1618.200000	1376.0	1860.4	2
270	1729.000000	1729.0	1729.0	1
300	1500.200000	1500.2	1500.2	1

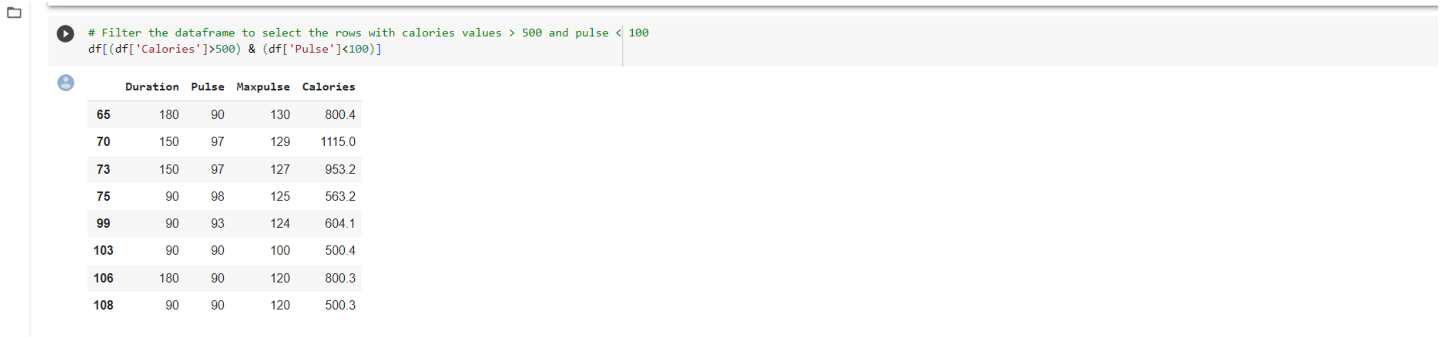
5. Filter the data frame to select the rows with calories values between 500 and1000



```
# Filter the dataframe to select the rows with calories values between 500 and 1000
df[(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
83	120	100	130	500.0
90	180	101	127	600.1
99	90	93	124	604.1
101	90	90	110	500.0
102	90	90	100	500.0
103	90	90	100	500.4
106	180	90	120	800.3
108	90	90	120	500.3

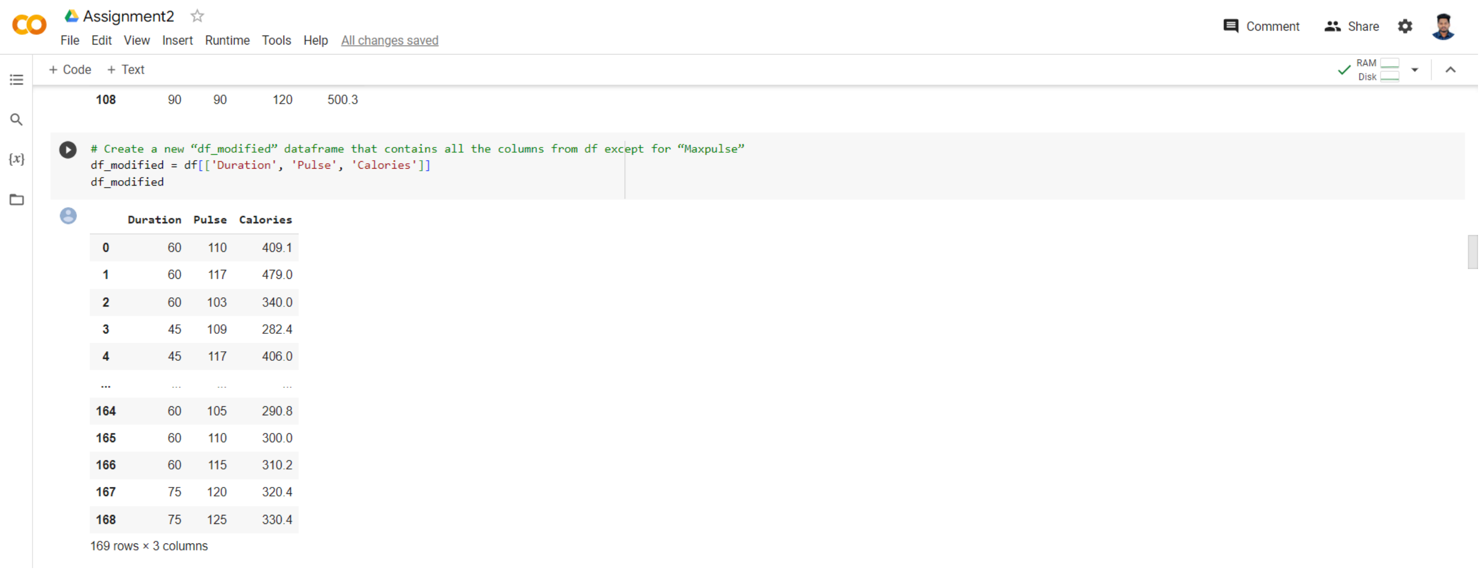
6. Filter the dataframe to select the rows with calories values > 500 and pulse <100



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



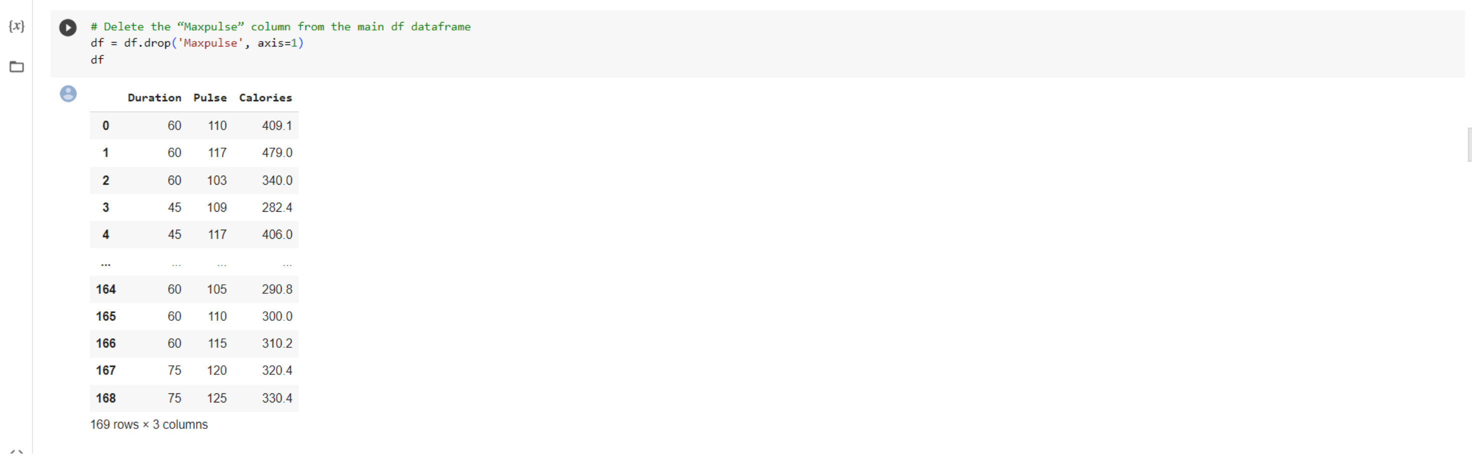
108	90	90	120	500.3

```
# Create a new "df_modified" dataframe that contains all the columns from df except for "Maxpulse"
df_modified = df[['Duration', 'Pulse', 'Calories']]
df_modified
```

	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
...	...	...	...
164	60	105	290.8
165	60	110	300.0
166	60	115	310.2
167	75	120	320.4
168	75	125	330.4

169 rows × 3 columns

8. Delete the "Maxpulse" column from the main df dataframe

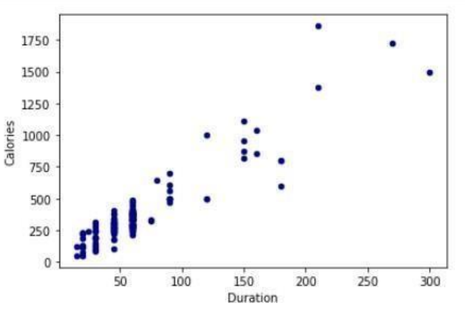


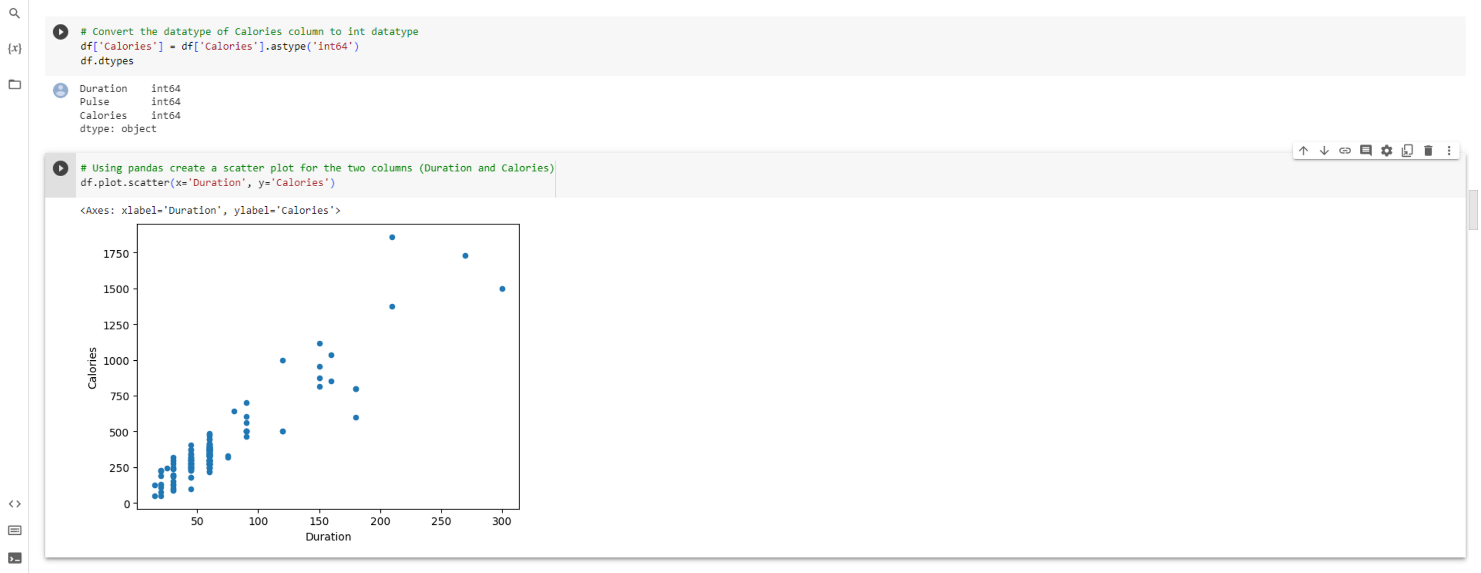
```
# Delete the "Maxpulse" column from the main df dataframe
df = df.drop('Maxpulse', axis=1)
df
```

	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
...	...	...	...
164	60	105	290.8
165	60	110	300.0
166	60	115	310.2
167	75	120	320.4
168	75	125	330.4

169 rows × 3 columns

9. Convert the datatype of Calories column to int datatype.
10. Using pandas create a scatter plot for the two columns (Duration and Calories).
    a. Example:

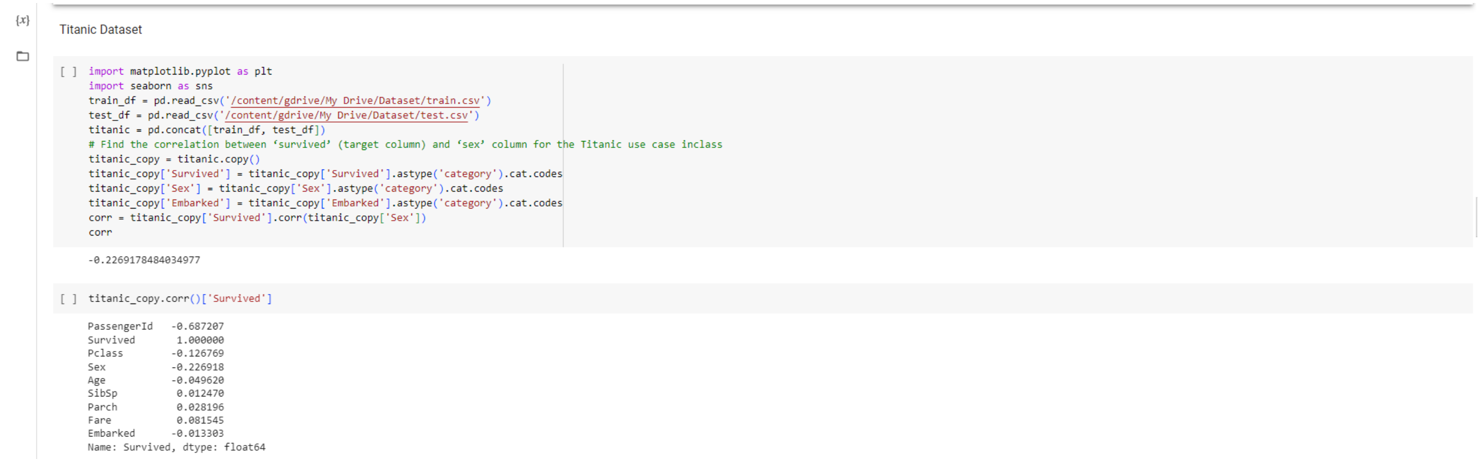



```
# Convert the datatype of Calories column to int datatype
df['Calories'] = df['Calories'].astype('int64')
df.dtypes
```

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

```
# Using pandas create a scatter plot for the two columns (Duration and Calories)
df.plot.scatter(x='Duration', y='Calories')
```

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

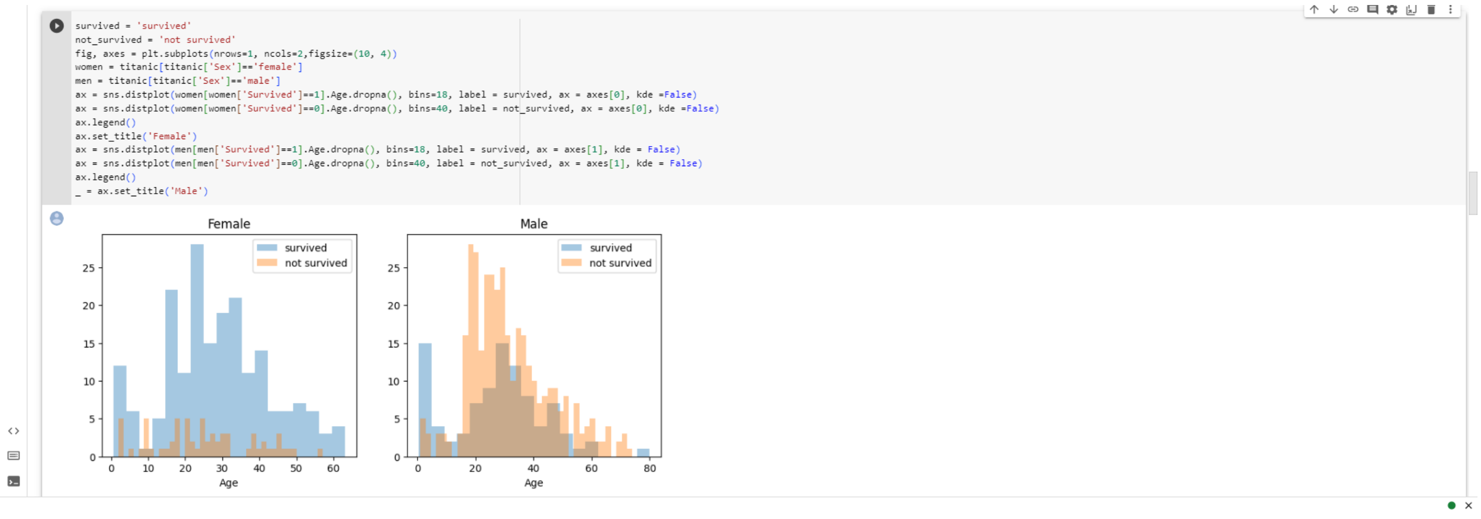

Titanic Dataset

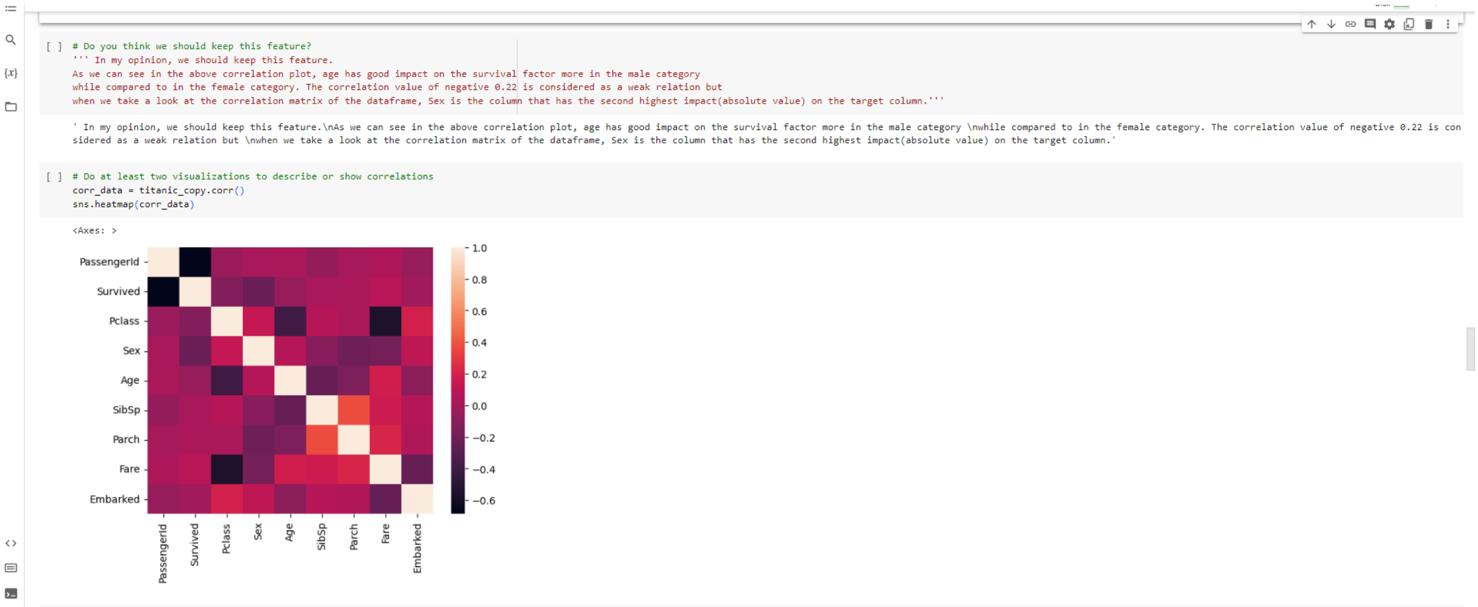
```
import matplotlib.pyplot as plt
import seaborn as sns
train_df = pd.read_csv('/content/gdrive/My Drive/Dataset/train.csv')
test_df = pd.read_csv('/content/gdrive/My Drive/Dataset/test.csv')
titanic = pd.concat([train_df, test_df])
# Find the correlation between ‘survived’ (target column) and ‘sex’ column for the Titanic use case inclass
titanic_copy = titanic.copy()
titanic_copy['Survived'] = titanic_copy['Survived'].astype('category').cat.codes
titanic_copy['Sex'] = titanic_copy['Sex'].astype('category').cat.codes
titanic_copy['Embarked'] = titanic_copy['Embarked'].astype('category').cat.codes
corr = titanic_copy['Survived'].corr(titanic_copy['Sex'])
corr
```

```
-0.2269178484034977
```

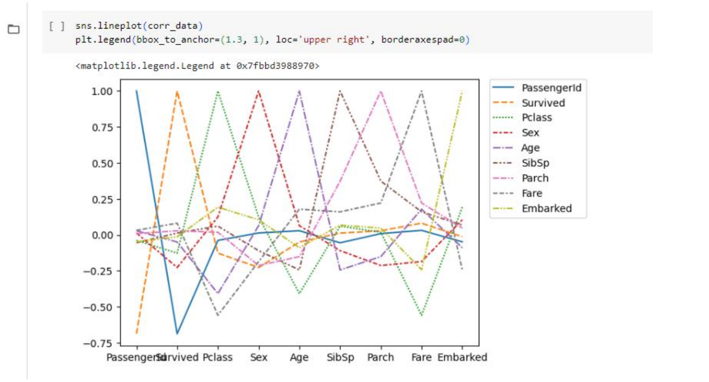
```
titanic_copy.corr()['Survived']
```

```
PassengerId   -0.687207
Survived       1.000000
Pclass        -0.126769
Sex           -0.226918
Age           -0.049620
SibSp          0.012470
Parch          0.028196
Fare           0.081545
Embarked      -0.013303
Name: Survived, dtype: float64
```

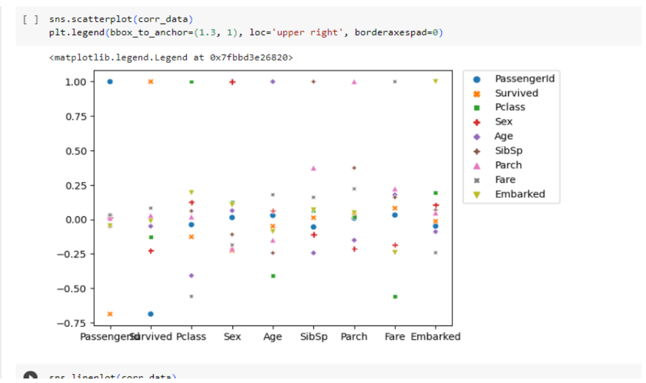

```
survived = 'survived'
not_survived = 'not survived'
fig, axes = plt.subplots(nrows=1, ncols=2,figsize=(10, 4))
women = titanic[titanic['Sex']=='female']
men = titanic[titanic['Sex']=='male']
ax = sns.distplot(women[women['Survived']==1].Age.dropna(), bins=18, label = survived, ax = axes[0], kde =False)
ax = sns.distplot(women[women['Survived']==0].Age.dropna(), bins=40, label = not_survived, ax = axes[0], kde =False)
ax.legend()
ax.set_title('Female')
ax = sns.distplot(men[men['Survived']==1].Age.dropna(), bins=18, label = survived, ax = axes[1], kde = False)
ax = sns.distplot(men[men['Survived']==0].Age.dropna(), bins=40, label = not_survived, ax = axes[1], kde = False)
ax.legend()
_ = ax.set_title('Male')
```



```
[ ] # Do you think we should keep this feature?
    ''' In my opinion, we should keep this feature.
    As we can see in the above correlation plot, age has good impact on the survival factor more in the male category
    while compared to in the female category. The correlation value of negative 0.22 is considered as a weak relation but
    when we take a look at the correlation matrix of the dataframe, Sex is the column that has the second highest impact(absolute value) on the target column.'''

    ' In my opinion, we should keep this feature.\nAs we can see in the above correlation plot, age has good impact on the survival factor more in the male category \nwhile compared to in the female category. The correlation value of negative 0.22 is con
    sidered as a weak relation but \nwhen we take a look at the correlation matrix of the dataframe, Sex is the column that has the second highest impact(absolute value) on the target column.'

[ ] # Do at least two visualizations to describe or show correlations
    corr_data = titanic_copy.corr()
    sns.heatmap(corr_data)

    <Axes: >
```



```
[ ] sns.lineplot(corr_data)
    plt.legend(bbox_to_anchor=(1.3, 1), loc='upper right', borderaxespad=0)

    <matplotlib.legend.Legend at 0x7fbbd3988970>
```



```
[ ] sns.scatterplot(corr_data)
    plt.legend(bbox_to_anchor=(1.3, 1), loc='upper right', borderaxespad=0)

    <matplotlib.legend.Legend at 0x7fbbd3e26820>
```

```
sns.lineplot(corr_data)
```

B. Scikit-learn

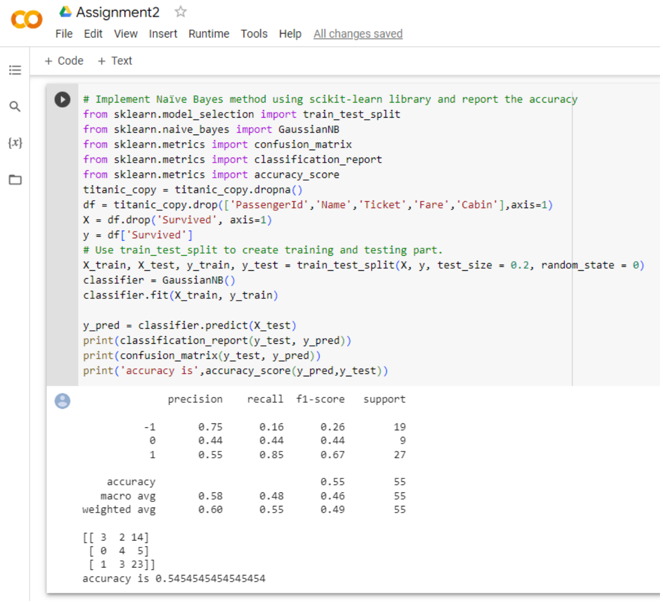
1. Implement Naïve Bayes method using scikit-learn library.
   a. Use the glass dataset available in Link also provided in your assignment.
   b. Use **train_test_split** to create training and testing part.
2. Evaluate the model on testing part using score and

```
classification_report(y_true, y_pred)
```

1. 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.
2. Evaluate the model on testing part using score and

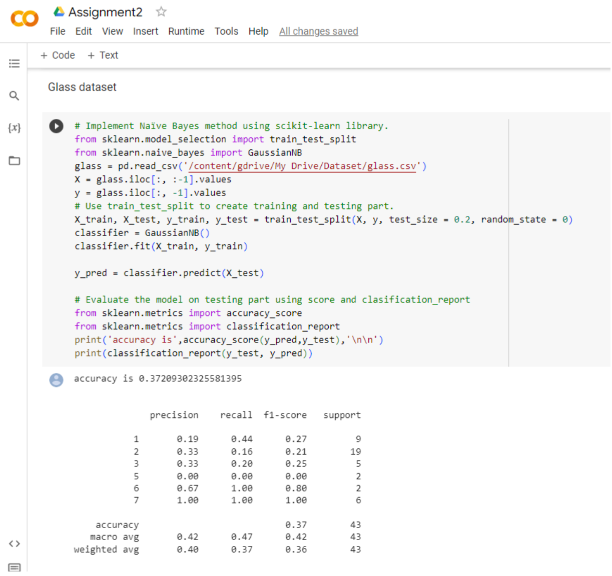
```
classification_report(y_true, y_pred)
```

Do at least two visualizations to describe or show correlations in the Glass Dataset. Which algorithm you got better accuracy? Can you justify why?



```
# Implement Naïve Bayes method using scikit-learn library and report the accuracy
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
titanic_copy = titanic_copy.dropna()
df = titanic_copy.drop(['PassengerId','Name','Ticket','Fare','Cabin'],axis=1)
X = df.drop('Survived', axis=1)
y = df['Survived']
# Use train_test_split to create training and testing part.
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
classifier = GaussianNB()
classifier.fit(X_train, y_train)

y_pred = classifier.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print('accuracy is',accuracy_score(y_pred,y_test))
```

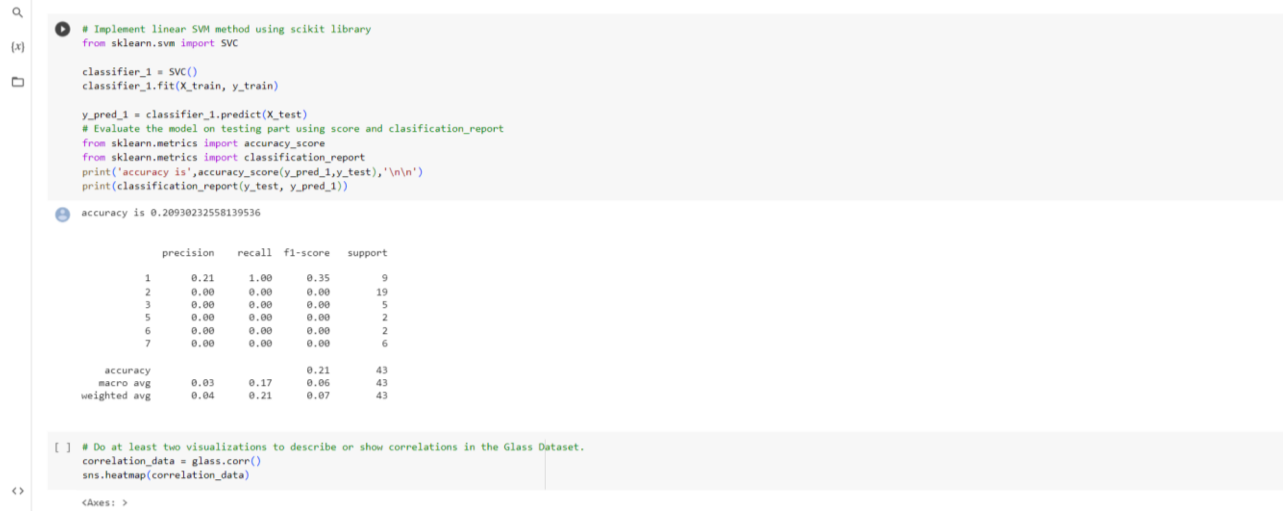
```
              precision    recall  f1-score   support

          -1       0.75      0.16      0.26        19
           0       0.44      0.44      0.44         9
           1       0.55      0.85      0.67        27

    accuracy                           0.55        55
   macro avg       0.58      0.48      0.46        55
weighted avg       0.60      0.55      0.49        55

[[ 3  2 14]
 [ 0  4  5]
 [ 1  3 23]]
accuracy is 0.5454545454545454
```



Glass dataset

```
# Implement Naïve Bayes method using scikit-learn library.
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
glass = pd.read_csv('/content/gdrive/My Drive/Dataset/glass.csv')
X = glass.iloc[:, :-1].values
y = glass.iloc[:, -1].values
# Use train_test_split to create training and testing part.
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
classifier = GaussianNB()
classifier.fit(X_train, y_train)

y_pred = classifier.predict(X_test)

# Evaluate the model on testing part using score and clasification_report
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
print('accuracy is',accuracy_score(y_pred,y_test),'\n\n')
print(classification_report(y_test, y_pred))
```

```
accuracy is 0.37209302325581395


              precision    recall  f1-score   support

           1       0.19      0.44      0.27         9
           2       0.33      0.16      0.21        19
           3       0.33      0.20      0.25         5
           5       0.00      0.00      0.00         2
           6       0.67      1.00      0.80         2
           7       1.00      1.00      1.00         6

    accuracy                           0.37        43
   macro avg       0.42      0.47      0.42        43
weighted avg       0.40      0.37      0.36        43
```

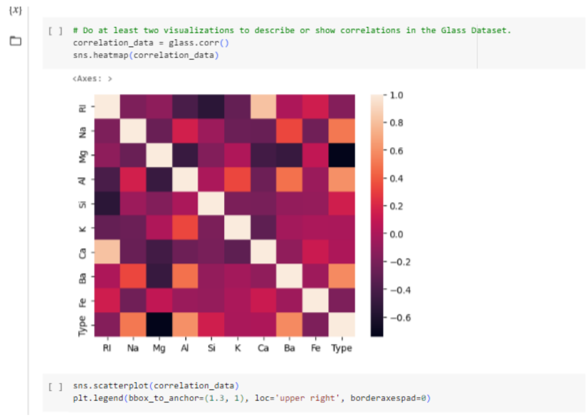


```
# Implement linear SVM method using scikit library
from sklearn.svm import SVC

classifier_1 = SVC()
classifier_1.fit(X_train, y_train)

y_pred_1 = classifier_1.predict(X_test)
# Evaluate the model on testing part using score and clasification_report
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
print('accuracy is',accuracy_score(y_pred_1,y_test),'\n\n')
print(classification_report(y_test, y_pred_1))
```

```
accuracy is 0.20930232558139536


              precision    recall  f1-score   support

           1       0.21      1.00      0.35         9
           2       0.00      0.00      0.00        19
           3       0.00      0.00      0.00         5
           5       0.00      0.00      0.00         2
           6       0.00      0.00      0.00         2
           7       0.00      0.00      0.00         6

    accuracy                           0.21        43
   macro avg       0.03      0.17      0.06        43
weighted avg       0.04      0.21      0.07        43
```

```
[ ] # Do at least two visualizations to describe or show correlations in the Glass Dataset.
    correlation_data = glass.corr()
    sns.heatmap(correlation_data)
```

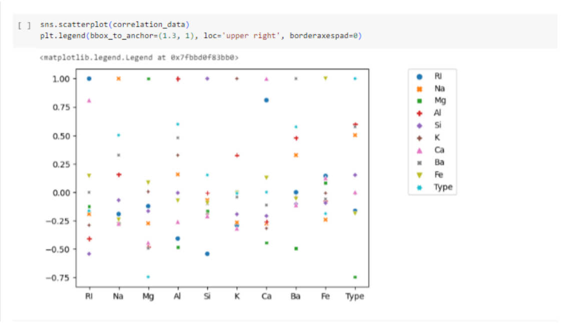
```
<Axes: >
```



```
[ ] # Do at least two visualizations to describe or show correlations in the Glass Dataset.
    correlation_data = glass.corr()
    sns.heatmap(correlation_data)
```

```
<Axes: >
```

```
[ ] sns.scatterplot(correlation_data)
    plt.legend(bbox_to_anchor=(1.3, 1), loc='upper right', borderaxespad=0)
```



```
[ ] sns.scatterplot(correlation_data)
    plt.legend(bbox_to_anchor=(1.3, 1), loc='upper right', borderaxespad=0)
```

```
<matplotlib.legend.Legend at 0x7fbbd0f83bb0>
```