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Video Link:

https://drive.google.com/file/d/1EPiKW39dVB9Ba3fdDAKKyB1A-ZNguEhN/view?usp=share link

GitHub Link:

https://github.com/AshokSai1999/Machine-Learning.git

## Q1) Pandas

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

60

45

45

```
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
                                      409.1
                                130
          1
                 60
                      117
                                145
                                      479.0
```

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

103

109

117

135

175

148

340.0

282.4 406.0

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.

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

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

#### 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)]</pre>
Out[9]:
               Duration Pulse Maxpulse Calories
                     80
                                            643 1
           51
                           123
                                     146
                    160
                          109
                                     135
                                            853.0
           62
                    180
                           90
                                     130
                                            800.4
           65
           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
                    180
                                     127
                                            600.1
           90
                           101
           99
                     90
                           93
                                     124
                                            604.1
           103
                     90
                           90
                                     100
                                            500.4
           106
                                     120
                                            800.3
                    180
                           90
           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)]</pre> Out[10]: Duration Pulse Maxpulse Calories 800.4 1115.0 953.2 563.2 604.1 500.4 800.3 500.3 

# 7. Create a new "df\_modified" dataframe that contains all the columns from df except for "Maxpulse".

409.1 479.0 340.0 282.4 406.0

## 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).

Duration

```
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'>
             1750
             1500
             1250
           Calories
             1000
              750
              500
              250
                                                      250
                                                              300
                        50
                               100
                                       150
                                               200
```

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

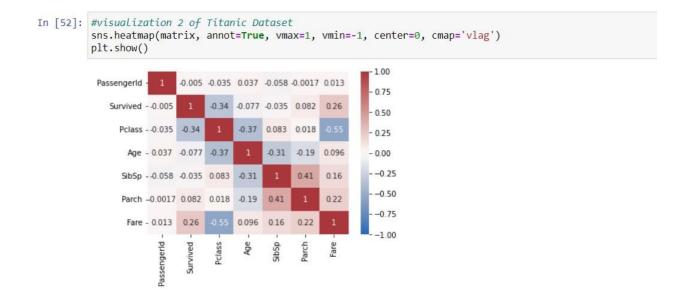
```
In [48]: #1.Titanic dataset
          import pandas as pd
          import seaborn as sns
          from sklearn import preprocessing
          import matplotlib.pyplot as plt
          df=pd.read csv("train.csv")
          df.head()
Out[48]:
             Passengerld Survived Pclass
                                                                          Name
                                                                                  Sex Age SibSp Parch
                                                                                                                   Ticket
                                                                                                                            Fare Cabin Embarked
                               0
                                                                                                                                              s
           0
                                      3
                                                            Braund, Mr. Owen Harris
                                                                                 male 22.0
                                                                                               1
                                                                                                      0
                                                                                                                A/5 21171
                                                                                                                          7.2500
                                                                                                                                  NaN
           1
                               1
                                      1 Cumings, Mrs. John Bradley (Florence Briggs Th... female 38.0
                                                                                               1
                                                                                                      0
                                                                                                                PC 17599 71.2833
                                                                                                                                  C85
                                                                                                                                              С
           2
                                     3
                                                                                                     0 STON/O2. 3101282 7.9250
                                                                                                                                              s
                      3
                               1
                                                             Heikkinen, Miss. Laina female 26.0
                                                                                               0
                                                                                                                                  NaN
                                                                                               1
                                                                                                      0
                                                                                                                                              S
           3
                               1
                                      1
                                             Futrelle, Mrs. Jacques Heath (Lily May Peel) female 35.0
                                                                                                                  113803 53.1000
                                                                                                                                 C123
                              0
                                      3
                                                 Allen, Mr. William Henry male 35.0 0 0
                                                                                                                  373450 8.0500
                                                                                                                                  NaN
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)
                                                                       SibSp
                       PassengerId Survived
                                                 Pclass
                                                                                  Parch
                          1.000000 -0.005007 -0.035144 0.036847 -0.057527 -0.001652
         PassengerId
                         -0.005007
                                   1.000000 -0.338481 -0.077221 -0.035322 0.081629
          Survived
         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
                         \hbox{-0.057527 -0.035322} \quad \hbox{0.083081 -0.308247} \quad \hbox{1.000000} \quad \hbox{0.414838}
                         -0.001652 0.081629 0.018443 -0.189119 0.414838 1.000000
          Parch
                          0.012658 0.257307 -0.549500 0.096067 0.159651 0.216225
         Fare
         PassengerId 0.012658
          Survived
                       0.257307
                      -0.549500
         Pclass
                       0.096067
          Age
          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]:
                                                                              SibSp
                                                                                                    Fare
                              Passengerld
                                            Survived
                                                        Pclass
                                                                                        Parch
                                                                     Age
                                 1.000000
                                           -0.005007
                                                      -0.035144
                                                                0.036847 -0.057527 -0.001652
                                                                                                0.012658
                 Passengerld
                                            1.000000
                                                      -0.338481 -0.077221 -0.035322 0.081629
                                                                                                0.257307
                    Survived
                                 -0.005007
                                 -0.035144 -0.338481
                                                      1.000000
                                                                -0.369226
                                                                           0.083081
                                                                                     0.018443
                                                                                               -0.549500
                      Pclass
                                 0.036847 -0.077221
                                                     -0.369226
                                                                1.000000
                                                                          -0.308247
                                                                                     -0.189119
                                                                                                0.096067
                        Age
                                 -0.057527
                                           -0.035322
                                                      0.083081
                                                                -0.308247
                                                                           1.000000
                                                                                     0.414838
                                                                                                0.159651
                       SibSp
                                 -0.001652
                                           0.081629
                                                      0.018443
                                                                -0.189119
                                                                                                0.216225
                                 0.216225
                                                                                                1.000000
```



#### 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]:

200	RI	Na	Mg	Al	Si	K	Ca	Ва	Fe	Туре
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
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

```
In [71]: #visualization 2 of Glass Dataset
            sns.heatmap(matrix, annot=True, vmax=1, vmin=-1, center=0, cmap='vlag')
            plt.show()
                                                                            1.00
                                -0.005 -0.035 0.037 -0.058 -0.0017 0.013
             Passengerid
                                                                            0.75
                Survived --0.005
                                       -0.34 -0.077 -0.035 0.082 0.26
                                                                            0.50
                                             -0.37 0.083 0.018
                  Pclass -- 0.035
                                -0.34
                                                                           - 0.25
                    Age - 0.037 -0.077 -0.37
                                                    -0.31
                                                         -0.19 0.096
                                                                           - 0.00
                                                                           --0.25
                                             -0.31
                                                           0.41
                   SibSp -- 0.058 -0.035 0.083
                                                                 0.16
                                                                            -0.50
                   Parch -0.0017 0.082 0.018 -0.19
                                                    0.41
                                                                 0.22
                                                                             -0.75
                    Fare - 0.013
                                0.26
                                             0.096
                                                    0.16
                                                           0.22
                                                                             -1.00
                           Passengerid
                                              Age
```

- 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	2: 55.81%			
Classification	Report:			
	precision	recall	f1-score	support
1 2	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	3 4 3
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)
```

Classificatio	n Report:			
	precision	recall	f1-score	support
1	0.37	1.00	0.54	11
1 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 7	0.00	0.00	0.00	4
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

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.