

Name: Pranav Kumar

Exp. No.: 4

PRN: 1032200232

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Aim: To Perform Exploratory Data Analysis on the given dataset.

Explanation:

Exploratory Data Analysis (EDA) is a crucial initial step in data analysis, aimed at gaining insights and understanding the dataset before diving into modeling or more advanced analyses. Here are five key points to explain the importance and goals of EDA:

1. **Data Understanding:** EDA helps you understand the dataset's structure, including its dimensions, variables, and data types. It reveals potential challenges, such as missing data, outliers, or inconsistencies, which need to be addressed during preprocessing.
2. **Pattern Discovery:** EDA enables the identification of patterns, trends, and relationships within the data. Visualization tools and statistical summaries help reveal data distributions, correlations, and potential clusters or groups.
3. **Insightful Visualizations:** EDA often involves creating visualizations (e.g., histograms, scatter plots, box plots) that provide intuitive insights into the data. These visualizations help communicate findings and patterns to stakeholders and guide further analysis.

Operations Performed are –

1. Handling Missing data
2. Filtering Data
3. Grouping Data
4. Finding the outliers
5. Etc.

Part A:

Program:

```
import pandas as pd

#Taking data
data = {'Name': ["Sam", "Kia", "Jack", "lilly", "Riya", "Keshav", "Rose"],
        'Age': [12, 13, 14, 13, 12, 14, 13],
        'Gender': ['M', 'F', 'M', 'F', 'F', 'M', 'F'],
        'Marks': [98, 97, 'Nan', 65, 74, 'Nan', 66]}
print(data)

#Making Dataframe
df = pd.DataFrame(data)
print(df)

#Checking null values
#print(df.isnull().sum())
#print(df.info())
#print(df.describe())

#calulate Average
c = avg = 0
for ele in df['Marks']:
    if str(ele).isnumeric():
        c += 1
        avg += ele
avg /= c
print('avg',avg)
print('c',c)

#Replace the null values with the average values
df = df.replace(to_replace = "Nan",
               value = avg)
print(df)

#objects
print(df.info())

#convert object to string
df['Gender'] = df['Gender'].map({'M': "Male",
                                'F': "Female"}).astype("string") #astype is type conversion from object
to string
print(df)
print(df.info())
```

```

#Data filtering
df = df[df['Marks'] >= 75]
print(df)

#data filtering - remove column
df = df.drop(['Age'], axis=1)
print(df)

#Add ID column to the existing table
data['ID'] = [101, 103, 105, 104, 102, 107, 106]
data1 = pd.DataFrame(data) #create dataframe again
print(data1)

#create table 2 with one column similar
data2 = pd.DataFrame({'ID': [101, 103, 105, 104, 102, 107, 106],
                      'Fee Status': ["Paid", "Unpaid", "Unpaid", "Unpaid", "Paid", "Unpaid", "Paid"]})
print(data2)

#merge the two tables using ID as the merging column
data3 = pd.merge(data1, data2, on="ID")
print(data3)

#make group of the data whose age is 13
grouped = data3.groupby('Age')
print(grouped.get_group(13))

```

Output:

```

('Name': ['Sam', 'Nia', 'Jack', 'Lilly', 'Niya', 'Keshav', 'Rose'], 'Age': [12, 13, 14, 13, 12, 14, 13], 'Gender': ['M', 'F', 'M', 'F', 'F', 'M', 'F'], 'Marks': [98, 97, 'NaN', 65, 74, 80, 66])
  Name  Age  Gender  Marks
0   Sam   12      M    98
1   Nia   13      F    97
2   Jack  14      M   NaN
3  Lilly  13      F    65
4  Niya  12      F    74
5 Keshav  14      M    80
6   Rose  13      F    66
avg 80.0
c 0
  Name  Age  Gender  Marks
0   Sam   12      M  98.0
1   Nia   13      F  97.0
2   Jack  14      M  80.0
3  Lilly  13      F  65.0
4  Niya  12      F  74.0
5 Keshav  14      M  80.0
6   Rose  13      F  66.0
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7 entries, 0 to 6
Data columns (total 4 columns):
 #   Column  Non-Null Count  Dtype
---  --
 0   Name    7 non-null         object
 1   Age     7 non-null         int64
 2   Gender  7 non-null         object
 3   Marks   7 non-null         float64

```

```

RangeIndex: 7 entries, 0 to 6
Data columns (total 4 columns):
 #   Column  Non-Null Count  Dtype
---  -
 0   Name    7 non-null      object
 1   Age     7 non-null      int64
 2   Gender  7 non-null      object
 3   Marks   7 non-null      float64
dtypes: float64(1), int64(1), object(2)
memory usage: 356.0+ bytes
None
   Name  Age  Gender  Marks
0   Sam   12    Male   98.8
1   Kia   13   Female   97.8
2   Jack  14    Male   80.0
3  Lilly  13   Female   65.0
4   Riya  12   Female   74.0
5  Keshav 14    Male   80.0
6   Rose  13   Female   66.8
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7 entries, 0 to 6
Data columns (total 4 columns):
 #   Column  Non-Null Count  Dtype
---  -
 0   Name    7 non-null      object
 1   Age     7 non-null      int64
 2   Gender  7 non-null      string
 3   Marks   7 non-null      float64
dtypes: float64(1), int64(1), object(1), string(1)

```

```

0   Name  Age  Gender  Marks  ID
0   Sam   12     M     98   101
1   Kia   13     F     97   103
2   Jack  14     M    Nan   105
3  Lilly  13     F     65   104
4   Riya  12     F     74   102
5  Keshav 14     M    Nan   107
6   Rose  13     F     66   106

   ID  Fee  Status
0  101    Paid
1  103  Unpaid
2  105  Unpaid
3  104  Unpaid
4  102    Paid
5  107  Unpaid
6  106    Paid

   Name  Age  Gender  Marks  ID  Fee  Status
0   Sam   12     M     98   101    Paid
1   Kia   13     F     97   103  Unpaid
2   Jack  14     M    Nan   105  Unpaid
3  Lilly  13     F     65   104  Unpaid
4   Riya  12     F     74   102    Paid
5  Keshav 14     M    Nan   107  Unpaid
6   Rose  13     F     66   106    Paid

   Name  Age  Gender  Marks  ID  Fee  Status
1   Kia   13     F     97   103  Unpaid
3  Lilly  13     F     65   104  Unpaid
6   Rose  13     F     66   106    Paid

```

Part B:

Program:

```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

import numpy as np


#open CSV file

df = pd.read_csv("titanic.csv")

print(df)


print(df.head())


df2 = df[['Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare']]

print(df2.head())


print(df2.isnull().sum())
```

```
print(df2.info())

updated_df1 = df2.dropna(axis=1)

print(updated_df1.info())

updated_df2 = df2.dropna(axis=0)

print(updated_df2.info())

print('skew', df2['Age'].skew())

#updated_df3 = df2

#updated_df3['Age'] = updated_df3['Age'].fillna(updated_df3['Age'].mean())

#print(updated_df3.info())

sample = [15,101,18,7,13,16,11,21,5,15,10,9,-1]

print('\n\nDifferent prog:')
```

```

print('mean',np.mean(sample))

print('median',np.median(sample))

print("sample",sample)

print("Q2 quantile of sample", np.median(sample))

print("Q1 quantile of sample", np.quantile(sample, .25))

print("Q3 quantile of sample", np.quantile(sample, .75))

plt.boxplot(sample, vert=False)

plt.show()

```

Output:

```

      PassengerId  Survived  Pclass  ...    Fare Cabin  Embarked
0             1         0       3  ...    7.2500   NaN        S
1             2         1       1  ...   71.2833   C85        C
2             3         1       3  ...    7.9250   NaN        S
3             4         1       1  ...   53.1000  C123        S
4             5         0       3  ...    8.0500   NaN        S
..          ...         ...     ...  ...     ...     ...        ...
886          887         0       2  ...   13.0000   NaN        S
887          888         1       1  ...   30.0000  B42        S
888          889         0       3  ...   23.4500   NaN        S
889          890         1       1  ...   30.0000  C148        C
890          891         0       3  ...    7.7500   NaN        Q

[891 rows x 12 columns]
      PassengerId  Survived  Pclass  ...    Fare Cabin  Embarked
0             1         0       3  ...    7.2500   NaN        S
1             2         1       1  ...   71.2833   C85        C
2             3         1       3  ...    7.9250   NaN        S
3             4         1       1  ...   53.1000  C123        S
4             5         0       3  ...    8.0500   NaN        S

[5 rows x 12 columns]
   Survived  Pclass   Sex  Age  SibSp  Parch    Fare
0         0       3  male  22.0     1     0    7.2500
1         1       1 female  38.0     1     0   71.2833
2         1       3 female  26.0     0     0    7.9250
3         1       1 female  35.0     1     0   53.1000
4         0       3  male  35.0     0     0    8.0500

```

```

Survived      0
Pclass        0
Sex            0
Age           177
SibSp          0
Parch          0
Fare           0
dtype: int64
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 7 columns):
#   Column      Non-Null Count  Dtype
---  ---
0   Survived    891 non-null    int64
1   Pclass      891 non-null    int64
2   Sex         891 non-null    object
3   Age         714 non-null    float64
4   SibSp       891 non-null    int64
5   Parch       891 non-null    int64
6   Fare        891 non-null    float64
dtypes: float64(2), int64(4), object(1)
memory usage: 48.9+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 6 columns):
#   Column      Non-Null Count  Dtype
---  ---
0   Survived    891 non-null    int64

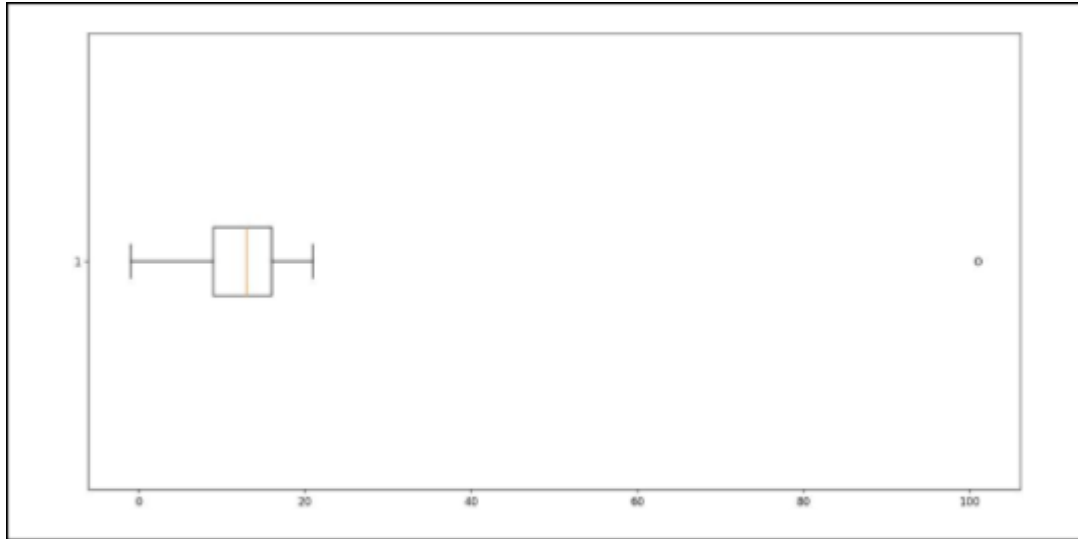
```

```

dtypes: float64(1), int64(4), object(1)
memory usage: 41.9+ KB
None
<class 'pandas.core.frame.DataFrame'>
Index: 714 entries, 0 to 890
Data columns (total 7 columns):
#   Column      Non-Null Count  Dtype
---  ---
0   Survived    714 non-null    int64
1   Pclass      714 non-null    int64
2   Sex         714 non-null    object
3   Age         714 non-null    float64
4   SibSp       714 non-null    int64
5   Parch       714 non-null    int64
6   Fare        714 non-null    float64
dtypes: float64(2), int64(4), object(1)
memory usage: 44.6+ KB
None
skew 0.38910778230882704

Different prog:
mean 18.46153846153846
median 13.0
sample [15, 101, 18, 7, 13, 16, 11, 21, 5, 15, 10, 9, -1]
Q2 quantile of sample 13.0
Q1 quantile of sample 9.0
Q3 quantile of sample 16.0

```


**Conclusion:**

From this experiment we learnt about Machine Learning and the different data processing techniques to make the data usage more efficient. We collected data and performed different data sorting and data analysis techniques. Code for the same was done successfully.

