```
#Dhiraj Wadile
#Roll no: 33391
#Batch: N11

import pandas as pd
import numpy as np
```

Importing dataset

```
df = pd.read_csv("Heart.csv")
```

```
df.head()
```

	Unnamed: 0	Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak
0	1	63	1	typical	145	233	1	2	150	0	2.3
1	2	67	1	asymptomatic	160	286	0	2	108	1	1.5
2	3	67	1	asymptomatic	120	229	0	2	129	1	2.6
3	4	37	1	nonanginal	130	250	0	0	187	0	3.5

Performing data analysis

```
df.shape
```

```
(303, 15)
```

Checking for null values

```
# checking for null values
df.isna().sum()
```

```
Unnamed: 0    0
Age           0
Sex           0
ChestPain     0
RestBP        0
Chol          0
Fbs           0
RestECG       0
MaxHR         0
ExAng         0
Oldpeak       0
Slope         0
Ca            4
Thal          2
AHD           0
dtype: int64
```

```
#total null values in the data set
df.isna().sum().sum()
```

```
6
```

Finding data type of each column

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 15 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  303 non-null    int64
 1   Age         303 non-null    int64
 2   Sex         303 non-null    int64
 3   ChestPain   303 non-null    object
 4   RestBP      303 non-null    int64
 5   Chol        303 non-null    int64
 6   Fbs         303 non-null    int64
```

```
 7   RestECG     303 non-null    int64
 8   MaxHR       303 non-null    int64
 9   ExAng       303 non-null    int64
 10  Oldpeak     303 non-null    float64
 11  Slope       303 non-null    int64
 12  Ca          299 non-null    float64
 13  Thal        301 non-null    object
 14  AHD         303 non-null    object
dtypes: float64(2), int64(10), object(3)
memory usage: 35.6+ KB
```

```
df.dtypes
```

```
Unnamed: 0      int64
Age             int64
Sex             int64
ChestPain      object
RestBP          int64
Chol            int64
Fbs             int64
RestECG         int64
MaxHR           int64
ExAng           int64
Oldpeak       float64
Slope           int64
Ca            float64
Thal           object
AHD            object
dtype: object
```

Finding number of zero's

```
(df==0).sum(axis=0)
```

```
Unnamed: 0      0
Age             0
Sex            97
ChestPain       0
RestBP          0
Chol            0
Fbs           258
RestECG       151
MaxHR           0
ExAng         204
Oldpeak        99
Slope           0
Ca            176
Thal            0
AHD             0
dtype: int64
```

Replacing missing values

```
# fill the value of column Ca with mean, because Ca is float data type
df['Ca'].fillna(value=df['Ca'].mean, inplace=True)
```

```
# fill the value of column Thal with mode value, because Thal is object
df['Thal'].fillna(value=df['Thal'].mode, inplace=True)
```

```
df.isna().sum().sum()
```

```
0
```

Finding mean age

```
print("Mean age is: ",df['Age'].mean())
```

```
Mean age is:  54.43894389438944
```

Visualization

```
import matplotlib.pyplot as plt
```

```
#visulizaing data for restbp based on age and sex
s = plt.scatter(df.Age, df.RestBP, c=df.Sex, label="RestBP")
plt.xlabel('Age')
plt.ylabel('RestBP')
plt.title("RestBP based on age and sex")
plt.legend(s.legend_elements()[0], list(set(df.Sex)))
plt.show()
```

Label encoding

```
from sklearn.preprocessing import LabelEncoder

labelEncoder = LabelEncoder()
df['ChestPain'] = labelEncoder.fit_transform(df['ChestPain'])

labelEncoder = LabelEncoder()
df['AHD'] = labelEncoder.fit_transform(df['AHD'])
```

Data spliting

```
X = df[['Age', 'Sex', 'ChestPain', 'RestBP', 'Chol']]
X.head()
```

	Age	Sex	ChestPain	RestBP	Chol
0	63	1	3	145	233
1	67	1	0	160	286
2	67	1	0	120	229
3	37	1	1	130	250
4	41	0	2	130	204

```
Y = df['AHD']
Y.head()
```

```
0    0
1    1
2    1
3    0
4    0
Name: AHD, dtype: int32
```

```
from sklearn.model_selection import train_test_split
```

```
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state=100, test_size=0.25)
```

```
print("X train shape: ", x_train.shape)
print("X test shape: ", x_test.shape)
print("Y train shape: ", y_train.shape)
print("Y test shape: ", y_test.shape)
```

```
X train shape:  (227, 5)
X test shape:  (76, 5)
Y train shape:  (227,)
Y test shape:  (76,)
```

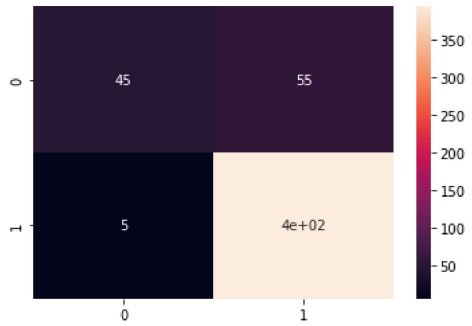
Confusion matrix

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
from numpy import array


cm = array([[45, 55], [5, 395]])


sns.heatmap(cm, annot=True)
```

```
<AxesSubplot:>
```



Scores

```
total = cm.sum()

#  accuracy is not a good metric when the data set is unbalanced
accuracy = np.diag(cm).sum() / total
print("Accuracy = ", accuracy)

# precision should be close to 1
precision = cm[0][0] / cm.sum(axis=1)[0]
print("Precision = ", round(precision, 4))

# recall should ideally be 1
# axis 1 means row wise, while axis 0 means column wise
recall = cm[0][0] / cm.sum(axis=0)[0]
print("Recall = ", recall)

# So ideally in a good classifier, we want both precision and recall to be one which also means FP and FN are zero.
# Therefore we need a metric that takes into account both precision and recall. F1-score is a metric which takes
# into account both precision and recall
f1 = 2 * ((precision*recall)/(precision+recall))
print("F1 score = ", round(f1, 3))
```

```
Accuracy =  0.88
Precision =  0.45
Recall =  0.9
F1 score =  0.6
```