ITA6016 MACHINE LEARNING LAB EXERCISE 1

Name: SIVAA V

Reg: 22MCA1127

1. Create two random numpy array of integers X and Y; check whether they are equal or not?

2. Create a numpy array with zeros and make it immutable and check whether able to change the values or not.

```
Code:
```

```
import numpy as np
arr=np.zeros(3,dtype=int)
arr.flags.writeable=False
print("Trying to change first value of array")
arr[0]=1
```

Screenshot:

Create a random numpy array Y of integers with size `10` and replace the maximum value by 100 and minimum value by 0.

```
Code:
import numpy as np
a=np.array([1,2,3])
print(a)
a[a.argmax()]=100
a[a.argmin()]=0
print("After replacing values")
print(a)
Screenshot:
```

```
In [3]: import numpy as np
    a=np.array([1,2,3])
    print(a)
    a[a.argmax()]=100
    a[a.argmin()]=0
    print("After replacing values")
    print(a)|

[1 2 3]
    After replacing values
    [ 0 2 100]
```

4. Write a program to find the closest value to a given value from a numpy array.

```
Code:
```

```
def find_closest(arr, val):
    idx = np.abs(arr - val).argmin()
    return arr[idx]
arr = np.array([1,7,10,12])
n=int(input("Enter a number "))
find_closest(arr, n)

In [7]: def find_closest(arr, val):
    idx = np.abs(arr - val).argmin
```

```
in [/]: def find_closest(arr, val):
    idx = np.abs(arr - val).argmin()
    return arr[idx]

arr = np.array([1,7,10,12])
n=int(input("Enter a number "))
find_closest(arr, n)

Enter a number 11
```

Out[7]: 10

5. Write a program to subtract the mean of each row of a matrix

Code:

```
import numpy as np
```

Y = np.array([1,2,3])

6. Write a program to convert the index of a series into a column of a dataframe.

Code:

```
import pandas as pd
d = pd.Series([10, 20, 30, 40, 50], index=['a', 'b', 'c', 'd', 'e'])
df = pd.DataFrame({'index_col': d.index, 'values': d.values})
print(df)
```

Screenshot:

7. Write a program to find out the items of series X not present in series Y?

Code:

import pandas as pd

X = pd.Series([1, 2, 3, 4, 5, 8])

```
Y = pd.Series([3, 4, 5, 6, 7, 9])
res = X[~X.isin(Y)]
print(res)
```

Screenshot:

```
In [4]: import pandas as pd

X = pd.Series([1, 2, 3, 4, 5, 8])
Y = pd.Series([3, 4, 5, 6, 7, 9])

result = X[~X.isin(Y)]

print(result)

0    1
1    2
5    8
dtype: int64
```

8. Write a program to find out the minimum, 25th percentile, median, 75th, and max of a numeric series?

Code:

```
import pandas as pd
import numpy as np
data = pd.Series(np.array([1,5,7,9,11,13,15]))
minimum = data.min()
q_25 = data.quantile(0.25)
median = data.median()
q_75 = data.quantile(0.75)
maximum = data.max()
print("Minimum:", minimum)
print("25th Percentile:", q_25)
```

```
print("Median:", median)
print("75th Percentile:", q_75)
print("Maximum:", maximum)
```

Screenshot:

```
In [9]: import pandas as pd
        import numpy as np
        data = pd.Series(np.array([1,5,7,9,11,13,15]))
        minimum = data.min()
        q 25 = data.quantile(0.25)
        median = data.median()
        q 75 = data.quantile(0.75)
        maximum = data.max()
        print("Minimum:", minimum)
        print("25th Percentile:", q 25)
        print("Median:", median)
        print("75th Percentile:", q 75)
        print("Maximum:", maximum)
        Minimum: 1
        25th Percentile: 6.0
        Median: 9.0
        75th Percentile: 12.0
        Maximum: 15
```

9. Write a program to keep only the top 2 most frequent values as it is and replace everything else as 'Other'?

Code:

```
import pandas as pd

data = pd.Series(['SIVAA V', '22MCA1127', 'SIVAA V', 'Arrange', 'New', 'Python'])

value_counts = data.value_counts()

top_values = value_counts.index[:2]

data[~data.isin(top_values)] = 'Other'

print(data)
```

Screenshot:

10. Write a program to convert the first character of each element in a series to uppercase

Code:

```
import pandas as pd
data = pd.Series([sivaa v, 'mca', 'vit'])
data = data.str.capitalize()
print(data)
```

Screenshot:

```
In [3]: #1
         import matplotlib.pyplot as plt
         experience=[2,3,5,13,8,16,11,1,9,4]
         pay=[15000, 28000, 42000, 64000, 50000, 90000, 58000, 8000, 54000, 30000]
         plt.scatter(experience,pay)
         plt.xlabel("Experience")
         plt.ylabel("Pay")
         plt.show()
            80000
            60000
            40000
           20000
                                              12
                                  Experience
In [36]: #2
         import numpy as np
         import pandas as pd
         x=[2,3,5,13,8,16,11,1,9,4]
         y=[15, 28, 42, 64, 50, 90, 58, 8, 54, 30]
         xmean=np.mean(x)
         ymean=np.mean(y)
         x_xmean=sum(x-xmean)
         y_ymean=sum(y-ymean)
         prod_x_y=x_xmean*y_ymean
         data={
             "x":x,
             "y":y,
             "x-xbar":x-xmean,
             "y-ybar":y-ymean,
             "(x-xbar)*(y-ybar)":prod_x_y,
             "(x-xbar)^2":(x-xmean)**2
         df=pd.DataFrame(data)
         print(df)
         print("Mean of x: ",xmean)
         print("Mean of y: ",ymean)
         print("Sumation of x-xbar: ",x_xmean)
         print("Sumation of y-ybar: ",y_ymean)
         print("Summation of (x-xbar)*(y-ybar): ", prod_x_y)
         print("Sumation of x-xbar^2: ", sum(x-xmean)**2)
             x y x-xbar y-ybar (x-xbar)*(y-ybar) (x-xbar)^2
            2 15
                                        -2.524355e-29
                                                            27.04
                           -28.9
                     -5.2
             3 28
                                        -2.524355e-29
                                                            17.64
                            -15.9
                      -4.2
                                        -2.524355e-29
                             -1.9
                                                             4.84
            5 42
                      -2.2
            13 64
                              20.1
                                        -2.524355e-29
                                                            33.64
                       5.8
            8
                                        -2.524355e-29
                                                             0.64
                50
                       0.8
                              6.1
                              46.1
                                        -2.524355e-29
                                                            77.44
            16
                90
                       8.8
                              14.1
                                                            14.44
            11
               58
                       3.8
                                        -2.524355e-29
             1
                8
                      -6.2
                             -35.9
                                        -2.524355e-29
                                                            38.44
                                        -2.524355e-29
             9
                54
                       1.8
                             10.1
                                                             3.24
         9 4 30
                      -3.2
                            -13.9
                                        -2.524355e-29
                                                            10.24
         Mean of x: 7.2
         Mean of y: 43.9
         Sumation of x-xbar: -1.7763568394002505e-15
         Sumation of y-ybar: 1.4210854715202004e-14
         Summation of (x-xbar)*(y-ybar): -2.524354896707238e-29
         Sumation of x-xbar^2: 3.1554436208840472e-30
         import numpy as np
         import pandas as pd
         x=[2,3,5,13,8,16,11,1,9,4]
         y=[15, 28, 42, 64, 50, 90, 58, 8, 54, 30]
         xmean=np.mean(x)
         ymean=np.mean(y)
         prod=(x-xmean)*(y-ymean)
         sum_prod=sum(prod)
         sq_x=(x-xmean)**2
         sq1=sum(sq_x)
         w1=sum_prod/sq1
         print("w1: ",w1)
         w0=ymean-w1*xmean
         print("w0: ",w0)
         w1: 4.776801405975396
         w0: 9.507029876977143
In [19]: #4
         import numpy as np
         import pandas as pd
         x=[]
         n=int(input("Enter number of elements for x: "))
         for i in range(0,n):
             ele=int(input())
             x.append(ele)
         n2=int(input("Enter number of elements for y: "))
         for i in range(0,n2):
             ele1=int(input())
             y.append(ele1)
         def calc(x,y):
             xmean=np.mean(x)
             ymean=np.mean(y)
             prod=(x-xmean)*(y-ymean)
             sum_prod=sum(prod)
             sq_x=(x-xmean)**2
             sq1=sum(sq_x)
             w1=sum_prod/sq1
             print("w1: ",w1)
             w0=ymean-w1*xmean
             print("w0: ",w0)
         calc(x,y)
         Enter number of elements for x: 3
         Enter number of elements for y: 3
         3
         w1: 1.0
         w0: 0.0
In [31]: #5
         import numpy as np
         import pandas as pd
         from sympy import symbols, Eq, solve
         y=[]
         n=int(input("Enter number of elements for x: "))
         for i in range(0,n):
             ele=int(input())
             x.append(ele)
         n2=int(input("Enter number of elements for y: "))
         for i in range(0,n2):
             ele1=int(input())
             y.append(ele1)
         def calc(x,y):
             b0, b1 = symbols('w0,w1')
             sum_x=sum(x)
             sum_y=sum(y)
             c=[]
             x_2=[]
             for i in range(0,n):
                 c.append(x[i]*y[i])
                 x_2.append(x[i]**2)
             calc1=sum(c)
             eq1=Eq(n*b0+b1*sum_x,sum_y)
             eq2=Eq(b0*sum(x)+b1*sum(x_2), calc1)
             print(solve((eq1,eq2),(b0,b1)))
         calc(x,y)
         Enter number of elements for x: 3
         1
         2
         Enter number of elements for y: 3
         1
         2
         {w0: 0, w1: 1}
In [30]: 11/6+1/12
         1.916666666666665
Out[30]:
In [49]: #6
         import numpy as num
         import random as rand
         def gradientDescent(X, Y, theta, alpha, a, numIterations):
             Xtrans = X.transpose()
             for i in range(0, numIterations):
                 hypothesis = num.dot(X, theta)
                 loss = hypothesis - Y
                 cst = num.sum(loss ** 2) / (2 * a)
                 gradient = num.dot(Xtrans, loss) / a
                 theta = theta - alpha * gradient
             return theta
         def genData(numPoints, bias, variance):
             X = num.zeros(shape=(numPoints, 3))
             Y = num.zeros(shape=numPoints)
             for i in range(0, numPoints):
                 X[i][0] = 2
                 X[i][1] = i
                 Y[i] = (i + bias) + rand.uniform(0, 2) * variance
             return X, Y
         X,Y = genData(90, 20, 9)
         a, b = num.shape(X)
         numIterations= 1
         alpha = 0.0004
         theta = num.ones(b)
         theta = gradientDescent(X,Y, theta, alpha,a, numIterations)
         print("w0: ",theta[0])
         print("w1: ",theta[1])
         w0: 1.0215475744298648
         w1: 1.475157085335912
In [54]: #7
         import pandas as pd
         import numpy as np
         from sklearn.model_selection import train_test_split
         from sklearn.linear_model import LinearRegression
         from sklearn.metrics import mean_squared_error
         from sklearn.metrics import mean_absolute_error
         import math
         data = \{'X': [2,3,5,13,8,16,11,1,9,4],
                 'Y': [15, 28, 42, 64, 50, 90, 58, 8, 54, 30]}
         df = pd.DataFrame(data)
         X_train, X_test, y_train, y_test = train_test_split(df['X'], df['Y'], test_size=0.2, random_state=0)
         X_{train} = np.array(X_{train}).reshape((-1, 1))
         X_{\text{test}} = \text{np.array}(X_{\text{test}}).\text{reshape}((-1, 1))
         model = LinearRegression()
         model.fit(X_train, y_train)
         y_pred = model.predict(X_test)
         print('Coefficients:', model.coef_)
         print('Intercept:', model.intercept_)
         df_result = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
         print(df_result)
         print("MSE: ", mean_squared_error(y_test, y_pred))
         print("RMSE: ", math.sqrt(mean_squared_error(y_test, y_pred)))
         print("MAE: ", mean_absolute_error(y_test, y_pred))
         Coefficients: [4.85307517]
         Intercept: 7.69020501138953
            Actual Predicted
                42 31.955581
                54 51.367882
         MSE: 53.909201643827025
         RMSE: 7.3422885835294585
         6.3382687927107035
```

Exercise_3_DecisionTree-Qn

In []:

```
#Name: SIVAA V
#Reg: 22MCA1127
```

In [1]:

```
import pandas as pd
import numpy as np
import math
```

In [2]:

```
data = pd.read_csv("/home/sivaa/Machine Learning/dataset.csv")
print(data)
```

```
Age Group Certified Skill Type
                                  Status
0
       Old
           Yes Soft Skill Rejected
1
    Middle
                 No Hard Skill Selected
2
    Middle
                Yes Soft Skill Rejected
3
                No Hard Skill Selected
    Young
4
    Middle
                Yes Hard Skill Rejected
                 No Soft Skill Selected
5
     Young
6
     Young
                Yes Soft Skill Selected
7
       Old
                 No Soft Skill Rejected
                 No Hard Skill Rejected
8
       Old
9
    Middle
                 No Soft Skill Selected
```

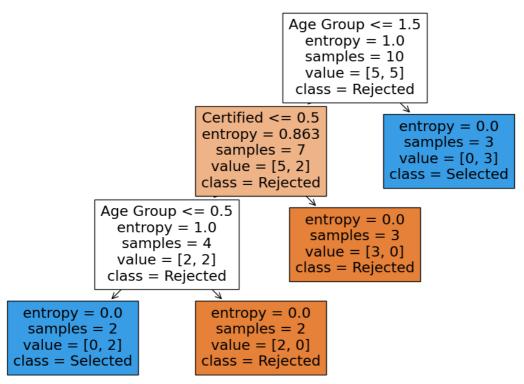
1. Consider the following dataset and calculate the entropy and information gain w.r.t the target attribute named "Status".

```
# Calculate the entropy of the target attribute "Status"
status_counts = data['Status'].value_counts()
num_instances = len(data)
entropy_status = 0
for count in status_counts:
    probability = count / num_instances
   entropy_status += -probability * math.log2(probability)
print(f"Entropy of Status: {entropy_status:.3f}")
# Calculate the information gain of each attribute w.r.t. the "Status" attribute
for attribute in ['Age Group', 'Certified', 'Skill Type']:
    entropy_attribute = 0
   attribute_value_counts = data[attribute].value_counts()
    for value, count in attribute_value_counts.items():
        value_subset = data[data[attribute] == value]
        value_subset_size = len(value_subset)
        value_status_counts = value_subset['Status'].value_counts()
        value_entropy_status = 0
        for value_count in value_status_counts:
            value_probability = value_count / value_subset_size
            value_entropy_status += -value_probability * math.log2(value_probability)
        entropy_attribute += count / num_instances * value_entropy_status
    information_gain = entropy_status - entropy_attribute
    print(f"Information gain of {attribute}: {information_gain:.3f}")
```

Entropy of Status: 1.000 Information gain of Age Group: 0.600 Information gain of Certified: 0.125 Information gain of Skill Type: 0.000

2. From the above calculated values of gain, design a decision tree for the above given data set.

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
data = pd.read_csv("/home/sivaa/Machine Learning/dataset.csv")
le = LabelEncoder()
data['Age Group'] = le.fit_transform(data['Age Group'])
data['Certified'] = le.fit_transform(data['Certified'])
data['Skill Type'] = le.fit_transform(data['Skill Type'])
data['Status'] = le.fit_transform(data['Status'])
dt = DecisionTreeClassifier(criterion='entropy')
X = data.drop('Status', axis=1)
y = data['Status']
dt.fit(X, y)
plt.figure(figsize=(12, 8))
plot_tree(dt, feature_names=X.columns, class_names=['Rejected', 'Selected'], filled=True)
plt.show()
```



3. Transform the designed decision tree into decision rules.

In [5]:

```
# Transform the decision tree into decision rules
def tree_to_rules(tree, feature_names):
    rules = []
    for feature in feature_names:
        for value in np.unique(data[feature]):
            threshold = np.mean(data[data[feature] == value]['Status'])
            rule = f"{feature} == {value} => Status = {'Selected' if threshold > 0.5 else
            rules.append(rule)
        return rules

# Print the decision rules
rules = tree_to_rules(dt, data.columns[:-1])
for rule in rules:
        print(rule)
```

```
Age Group == 0 => Status = Rejected
Age Group == 1 => Status = Rejected
Age Group == 2 => Status = Selected
Certified == 0 => Status = Selected
Certified == 1 => Status = Rejected
Skill Type == 0 => Status = Rejected
Skill Type == 1 => Status = Rejected
```

4. Use the designed decision tree or rules to predict the 'Status' of the given employee. • Young No Hard Skill • Old Yes Soft Skill • Middle Yes Hard Skill

In [6]:

```
from sklearn.tree import DecisionTreeClassifier, export_text
from sklearn.preprocessing import LabelEncoder
import pandas as pd

data = pd.read_csv("/home/sivaa/Machine Learning/dataset.csv")

le = LabelEncoder()
data['Age Group'] = le.fit_transform(data['Age Group'])
data['Certified'] = le.fit_transform(data['Certified'])
data['Skill Type'] = le.fit_transform(data['Skill Type'])
data['Status'] = le.fit_transform(data['Status'])

dt = DecisionTreeClassifier(criterion='entropy')
X = data.drop('Status', axis=1)
y = data['Status']
dt.fit(X, y)

tree_rules = export_text(dt, feature_names=X.columns.tolist())
print(tree_rules)
```

```
|--- Age Group <= 1.50
| |--- Age Group <= 0.50
| | |--- Certified <= 0.50
| | |--- class: 1
| | |--- Certified > 0.50
| | |--- class: 0
| |--- Age Group > 0.50
| |--- class: 0
|--- Age Group > 1.50
| |--- class: 1
```

5. Design a function named find_entropy in python for finding the entropy of the attributes given in the above dataset.

In [7]:

```
import pandas as pd
import math

data = pd.read_csv("/home/sivaa/Machine Learning/dataset.csv")

def find_entropy(df, attribute):
    value_counts = df[attribute].value_counts()

    total_instances = len(df)
    entropy = 0

for value_count in value_counts:
    probability = value_count / total_instances
    entropy -= probability * math.log2(probability)

    return entropy

entropy = find_entropy(data, 'Age Group')
print(f"Entropy of 'Age Group': {entropy}")
```

Entropy of 'Age Group': 1.5709505944546684

6. Design a function named find_gain in python for finding the information gain of the attributes given in the above dataset w.r.t to the 'Status' attribute

In [8]:

```
import math
def find_entropy(df):
   entropy = 0
   num_records = len(df)
   classes = df['Status'].unique()
   for c in classes:
        num c = len(df[df['Status']==c])
        p = num_c/num_records
        entropy -= p * math.log2(p)
   return entropy
def find_gain(df, attribute):
   total entropy = find entropy(df)
   values = df[attribute].unique()
   entropy = 0
   for v in values:
        num_v = len(df[df[attribute]==v])
        df v = df[df[attribute]==v]
        entropy += (num_v/len(df))*find_entropy(df_v)
   gain = total entropy - entropy
   return gain
find entropy(data)
find_gain(data, 'Status')
```

Out[8]:

7. Load the above dataset as data frame in python

In [9]:

```
import pandas as pd

data = pd.DataFrame({
    'Age Group': ['Old', 'Middle', 'Middle', 'Young', 'Middle', 'Young', 'Young', 'Old',
    'Certified': ['Yes', 'No', 'Yes', 'No', 'Yes', 'No', 'No', 'No'],
    'Skill Type': ['Soft Skill', 'Hard Skill', 'Soft Skill', 'Hard Skill',
    'Status': ['Rejected', 'Selected', 'Rejected', 'Selected', 'Selected
```

8. Design and visualize the decision tree using scikit learn package for the given dataset.

In [10]:

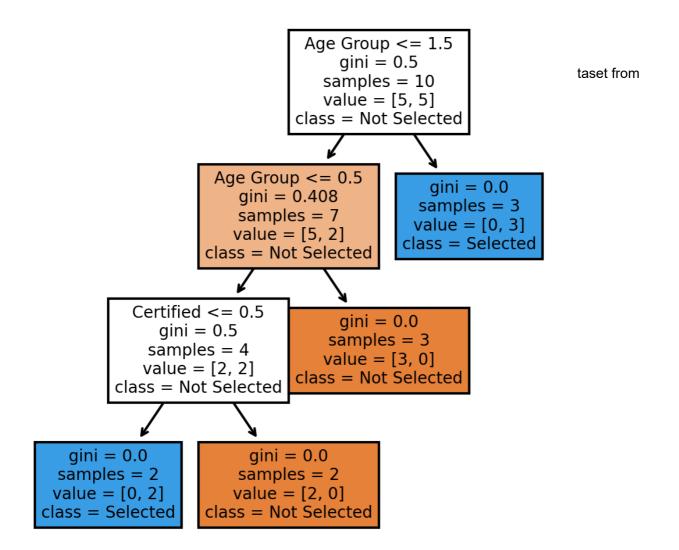
```
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
import matplotlib.pyplot as plt

model = DecisionTreeClassifier()

model.fit(X, y)

fig, axes = plt.subplots(nrows=1, ncols=1, figsize=(4,4), dpi=300)
tree.plot_tree(model, feature_names=X.columns, class_names=['Not Selected', 'Selected'],
```

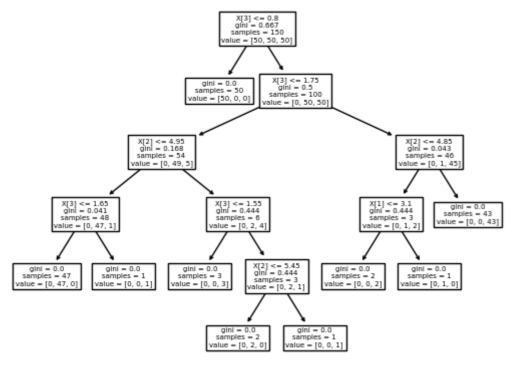
Out[10]:



In [11]:

```
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot tree
iris = load_iris()
iris_df = pd.DataFrame(iris.data, columns=iris.feature_names)
iris df['target'] = iris.target
X = iris df.iloc[:, :-1]
y = iris_df.iloc[:, -1]
tree = DecisionTreeClassifier()
tree.fit(X, y)
plot_tree(tree)
```

```
Out[11]:
[Text(0.5, 0.9166666666666666, 'X[3] <= 0.8\ngini = 0.667\nsamples = 150\n
value = [50, 50, 50]'),
   Text(0.4230769230769231, 0.75, 'gini = 0.0 \nsamples = 50 \nvalue = [50, 0, 0]
0]'),
    Text(0.5769230769230769, 0.75, 'X[3] \leftarrow 1.75 \cdot ngini = 0.5 \cdot nsamples = 100 \cdot nsamples = 1
value = [0, 50, 50]'),
    nsamples = 54 nvalue = [0, 49, 5]'),
    Text(0.15384615384615385, 0.416666666666667, 'X[3] <= 1.65 \ngini = 0.041
\nsamples = 48\nvalue = [0, 47, 1]'),
   Text(0.07692307692307693, 0.25, 'gini = 0.0 \nsamples = 47 \nvalue = [0, 4]
7, 0]'),
   Text(0.23076923076923078, 0.25, 'gini = 0.0 \nsamples = 1 \nvalue = [0, 0, 0]
1]'),
    Text(0.46153846153846156, 0.4166666666666667, 'X[3] <= 1.55 \setminus injury = 0.444
\nsamples = 6\nvalue = [0, 2, 4]'),
   Text(0.38461538461538464, 0.25, 'gini = 0.0 \nsamples = 3 \nvalue = [0, 0, 0]
3]'),
    Text(0.5384615384615384, 0.25, 'X[2] <= 5.45 \setminus i = 0.444 \setminus samples = 3 \setminus samples = 3 \setminus i = 0.444 \setminus samples = 3 \setminus i = 0.444 \setminus samples = 3 \setminus sam
value = [0, 2, 1]'),
    Text(0.46153846153846156, 0.08333333333333333, 'gini = 0.0 \nsamples = 2 \n
value = [0, 2, 0]'),
    Text(0.6153846153846154, 0.083333333333333333, 'gini = 0.0 \nsamples = 1 \nv
alue = [0, 0, 1]'),
    Text(0.8461538461538461, 0.583333333333334, 'X[2] <= 4.85 \cdot ngini = 0.043
\nsamples = 46\nvalue = [0, 1, 45]'),
   samples = 3\nvalue = [0, 1, 2]'),
   Text(0.6923076923076923, 0.25, 'gini = 0.0\nsamples = 2\nvalue = [0, 0, 0]
2]'),
   Text(0.8461538461538461, 0.25, 'gini = 0.0 \nsamples = 1 \nvalue = [0, 1, 1]
0]'),
   alue = [0, 0, 43]')
```



In [12]:

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.model_selection import train_test_split
df = pd.read_csv('iris.csv')
X = df.drop(['Species'], axis=1)
y = df['Species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
tree = DecisionTreeClassifier(random_state=42)
tree.fit(X_train, y_train)
y_pred = tree.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
```

Accuracy: 1.0 Precision: 1.0 Recall: 1.0 F1 Score: 1.0

In []:

#Name: SIVAA V
#Reg: 22MCA1127
#Exercise: 4

In [4]:

#1. Load the Titanic dataset from Kaggle to working environment.

import pandas as pd
train_data = pd.read_csv("/home/sivaa/Machine Learning/train.csv")

In [5]:

#2. Perform exploratory analysis on the loaded dataset and draw your inferences.
train_data.head()

Out[5]:

	Passengerld	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500
4										•

In [6]:

#2. Perform exploratory analysis on the loaded dataset and draw your inferences.

train_data.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 891 entries, 0 to 890 Data columns (total 12 columns):

#	Column	Non-Null Count	Dtype			
0	PassengerId	891 non-null	int64			
1	Survived	891 non-null	int64			
2	Pclass	891 non-null	int64			
3	Name	891 non-null	object			
4	Sex	891 non-null	object			
5	Age	714 non-null	float64			
6	SibSp	891 non-null	int64			
7	Parch	891 non-null	int64			
8	Ticket	891 non-null	object			
9	Fare	891 non-null	float64			
10	Cabin	204 non-null	object			
11	Embarked	889 non-null	object			
dtynes: float64(2), int64(5), object(5)						

dtypes: float64(2), int64(5), object(5)

memory usage: 83.7+ KB

In [7]:

#2. Perform exploratory analysis on the loaded dataset and draw your inferences.

train_data.describe()

Out[7]:

	Passengerld	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [8]:

#3. From the above analysis if any attributes are not relevant in accessing the survival #of the passenger then drop those columns.

```
train_data = train_data.drop(['PassengerId','Name','Ticket','Cabin'],axis=1)
train_data.head()
```

Out[8]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.2500	S
1	1	1	female	38.0	1	0	71.2833	С
2	1	3	female	26.0	0	0	7.9250	S
3	1	1	female	35.0	1	0	53.1000	S
4	0	3	male	35.0	0	0	8.0500	S

In [10]:

```
#4.Check for the missing values in the modified dataset and fill the missing
# values with appropriate methods.

train_data.isnull().sum()
median = train_data['Age'].median()
train_data['Age'].fillna(median,inplace=True)
mode_embarked = train_data['Embarked'].mode()[0]
train_data['Embarked'].fillna(mode_embarked, inplace=True)
train_data.isnull().sum()
```

Out[10]:

Survived	0
Pclass	0
Sex	0
Age	0
SibSp	0
Parch	0
Fare	0
Embarked	0
dtype: int64	Ļ

In [24]:

```
#5. Split the modified dataset into 80-20 ratio for training and testing.
from sklearn.model_selection import train_test_split

x = train_data.drop('Survived', axis=1)
y = train_data['Survived']
features = ["Pclass", "Sex", "SibSp", "Parch"]
x = pd.get_dummies(train_data[features])

print(x)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
```

	Pclass	SibSp	Parch	Sex_female	Sex_male
0	3	1	0	0	1
1	1	1	0	1	0
2	3	0	0	1	0
3	1	1	0	1	0
4	3	0	0	0	1
• •	• • •	• • •		• • •	• • •
886	2	0	0	0	1
887	1	0	0	1	0
888	3	1	2	1	0
889	1	0	0	0	1
890	3	0	0	0	1

[891 rows x 5 columns]

In [25]:

```
#6. Apply Logistic Regression and design a model on the training data.
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
model = LogisticRegression()
model.fit(x_train, y_train)
```

Accuracy of the logistic regression model: 79.33%

In [26]:

```
#7 Fit the created model on the test data.

y_pred = model.predict(x_test)

accuracy = accuracy_score(y_test, y_pred)

print("Accuracy of the logistic regression model: {:.2f}%".format(accuracy * 100))
```

Accuracy of the logistic regression model: 79.33%

In []:			

In []:

```
#Name: SIVAA V
#Reg: 22MCA1127
#Lab Exercise: 5
```

In [5]:

```
#1. Load the salary dataset to working environment.
import pandas as pd
train_data = pd.read_csv("C:/Users/student/Downloads/position_salaries.csv")
```

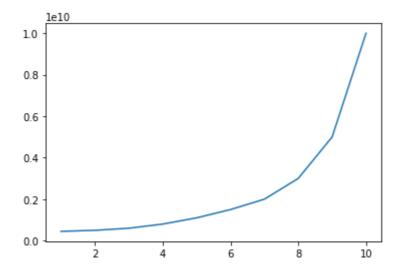
In [14]:

```
# 2. Perform exploratory analysis on the Loaded dataset and draw your inferences
import matplotlib.pyplot as plt

x = train_data["Years of Experience"]
y = train_data["Salary"]
y_val = y*10000
plt.plot(x,y_val)
```

Out[14]:

[<matplotlib.lines.Line2D at 0x1ce853269d0>]



In []:

3. Apply Linear Regression and design a model on the training data. import LinearRegression

```
In [ ]:
```

```
#Name: SIVAA V
#Reg: 22MCA1127
#Lab Exercise: 6
```

In [23]:

```
#Load the breast cancer dataset form sklearn.
from sklearn.datasets import load_breast_cancer
data = load_breast_cancer()
```

In [24]:

```
#If require perform data preprocessing.
from sklearn.preprocessing import StandardScaler

x= data.data
y = data.target
scaler = StandardScaler()
X = scaler.fit_transform(x)
```

In [25]:

```
#Split the dataset into training and testing by 90:10 ratios
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, random_state=10)
```

In [26]:

```
#Apply linear SVM on the training dataset.
from sklearn.svm import LinearSVC
svm = LinearSVC()
svm.fit(X_train, y_train)
```

Out[26]:

LinearSVC()

In [27]:

```
#Use the above model and fit the test dataset.
y_predicted = svm.predict(X_test)
```

```
In [28]:
#Display the accuracy and confusion matrix of evaluated model on test data.
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test, y_predicted)
print("Accuracy:", accuracy)
Accuracy: 0.9473684210526315
In [53]:
#Apply SVM on the training dataset using polynomial kernel.
from sklearn.svm import SVC
svm = SVC(kernel='poly', degree=3)
svm.fit(X_train, y_train)
Out[53]:
SVC(kernel='poly')
In [54]:
#Use the above model and fit the test dataset.
y_predicted_poly = svm.predict(X_test)
In [55]:
#Display the accuracy and confusion matrix of evaluated model on test data
accuracy = accuracy_score(y_test, y_predicted_poly)
print("Accuracy:", accuracy)
Accuracy: 0.8771929824561403
In [56]:
#Apply SVM on the training dataset using RBF kernel.
svm = SVC(kernel='rbf')
svm.fit(X_train, y_train)
Out[56]:
SVC()
In [57]:
```

#Use the above model and fit the test dataset.

y_predicted_rbf = svm.predict(X_test)

```
In [58]:
```

```
#Display the accuracy and confusion matrix of evaluated model on test data
accuracy = accuracy_score(y_test, y_predicted_rbf)
print("Accuracy:", accuracy)
```

Accuracy: 0.9649122807017544

In []:

```
In [ ]:
```

```
#Name: SIVAA V
#Reg; 22MCA1127
#Lab Exercise: 7
```

In [79]:

```
#1.Load the dataset (iris.csv).
import pandas as pd
data = pd.read_csv("C:/Users/student/Downloads/archive/Iris.csv")
print(data)
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	\
0	1	5.1	3.5	1.4	0.2	
1	2	4.9	3.0	1.4	0.2	
2	3	4.7	3.2	1.3	0.2	
3	4	4.6	3.1	1.5	0.2	
4	5	5.0	3.6	1.4	0.2	
		• • •		• • •	• • •	
145	146	6.7	3.0	5.2	2.3	
146	147	6.3	2.5	5.0	1.9	
147	148	6.5	3.0	5.2	2.0	
148	149	6.2	3.4	5.4	2.3	
149	150	5.9	3.0	5.1	1.8	

```
Species
        Iris-setosa
0
        Iris-setosa
1
2
        Iris-setosa
3
        Iris-setosa
4
        Iris-setosa
. .
145 Iris-virginica
146 Iris-virginica
147 Iris-virginica
148
    Iris-virginica
    Iris-virginica
149
```

[150 rows x 6 columns]

In [80]:

```
#2.Split dataset into test and train (20:80)
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(data.drop('Species', axis=1), data['State of the content of t
```

In [81]:

```
#3.Build KNN classifier with k value as 2 for identifying the flower Species
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=2)
knn.fit(X_train, y_train)
y_pred_2 = knn.predict(X_test)
```

```
In [82]:
```

```
#4.Build KNN classifier with k value as 4 for identifying the flower Species.
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=4)
knn.fit(X_train, y_train)
y_pred_4 = knn.predict(X_test)
```

In [83]:

```
#5. Evaluate the step-3 and step-4.

print("Predicted values for Step-3")

print(y_pred_2)

print("\nPredicted values for Step-4")

print(y_pred_4)

Predicted values for Step-3

['Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-virginica'

'Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-versicolor'

'Iris-versicolor' 'Iris-versicolor' 'Iris-virginica' 'Iris-versicolor'

'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa'

'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa'

'Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa'

'Iris-virginica' 'Iris-setosa' 'Iris-setosa' 'Iris-versicolor'

'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor'

'Iris-versicolor' 'Iris-setosa']
```

```
Predicted values for Step-4

['Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-virginica'
  'Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-versicolor'
  'Iris-versicolor' 'Iris-versicolor' 'Iris-versicolor'
  'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa'
  'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa'
  'Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa'
  'Iris-virginica' 'Iris-setosa' 'Iris-setosa' 'Iris-versicolor'
  'Iris-versicolor' 'Iris-setosa']
```

In [84]:

```
#6.Design a method for calculating the distance between data points for the given dataset
import numpy as np

def euclidean_distance(x1, x2):
    return np.sqrt(np.sum((x1 - x2)**2))
d = euclidean_distance(X_train['SepalLengthCm'],X_train['SepalWidthCm'])
print(d)
```

32.75561020649745

```
#7. Design a method for finding the nearest neighbours of a given data point using the ab
import numpy as np

def find_nearest_neighbor(X, y, x_query):
    distances = []
    for i, x in enumerate(X):
        distance = euclidean_distance(x, x_query)
        distances.append((distance, y[i]))
    distances.sort()
    return distances[0][1]

y_pred=[]
for i, x in enumerate(X_test):
    y_pred.append(find_nearest_neighbor(X_train, y_train, x))
print(y_pred)
```

[51.732763231999996, 22.89749796, 59.09498796, 35.3011712, 10.535882756, 4 4.27814872, 23.696600644, 51.0556978, 26.310404159999997, 48.79421652, 27. 827251359999998, 18.28490352, 54.896079119999996, 28.296095039999997, 38.2 0386516, 39.699338604, 40.062002979999995, 9.731264264, 37.171030112, 31.8 12422639999998, 32.051670812, 36.56291228, 45.08483564, 15.74832131599999 8, 18.01600788, 50.60064364, 17.3403214, 41.053469468, 59.30183076, 20.966 96516, 37.437857324, 27.742445811999996, 41.684340008, 46.2293658, 19.4156 4416, 37.721921436, 26.310404159999997, 33.798802996, 27.874825204, 47.401 475, 26.848195439999998, 10.089791784, 43.25082948, 46.68441996, 13.355150 12, 77.29715436, 59.494884039999995, 41.244454319999996, 27.53077668, 10.3 938507, 57.21823428799999, 39.700028079999996, 24.3385028, 27.935499091999 997, 69.83702404, 46.20178676, 26.310404159999997, 11.483912255999998, 38. 56239268, 19.691434559999998, 33.798802996, 15.615941924, 40.85834776, 36. 3009114, 15.030576799999999, 18.033934256, 33.398217439999996, 12.18097249 2, 39.64487, 13.12072828, 14.596896395999998, 10.787541496, 11.36256448, 2 7.827251359999998, 26.147687824, 24.44881896, 56.141962252, 51.0556978, 5 7.91598399999995, 8.06342182, 39.358047983999995, 28.096147, 34.6806428, 39.64487, 43.698299404, 35.3011712, 44.61185510399999, 33.7153764, 7.31534 0359999995, 22.31833812, 31.84000168, 73.69808963999999, 9.4458212, 56.61 9079643999996, 46.234192132, 46.931941843999994, 19.519065559999998, 40.23 09246, 39.58281716, 37.231704, 24.065470304, 43.798273423999994, 33.116911 232, 24.00065956, 69.29923276, 12.052040479999999, 50.93848688, 30.1232064 4, 45.939785879999995, 67.69964844, 44.296075096, 45.08483564, 32.82319445 6, 44.27814872, 35.75425543054136, 55.25460664, 22.53207568, 33.75674496, 55.50971276, 46.234192132, 17.236210524, 21.946021079999998, 46.6430514, 2 7.33772339999998, 24.57981939999998, 31.2677366, 52.61391356, 49.2010073 6, 42.13387836, 32.39847724, 11.483912255999998, 23.13881456, 7.8393421199 999995, 65.99664272, 10.222171176, 41.15137506, 17.43684804, 45.83636448, 22.94576128, 37.363393916, 21.29101888, 31.178794196000002, 38.20386516, 3 4.6806428, 46.234192132, 43.57833058, 26.8550902, 13.19657064, 27.87482520 4, 14.2032056, 34.73580088, 15.52010475999999, 45.89841732, 21.29101888, 48.67011084, 42.347615919999996, 23.835874796, 61.921839559999995, 22.8974 9796, 41.053469468, 9.131420144, 45.69846928, 34.67374804, 55.064311264, 3 3.398217439999996, 68.75060685418796, 37.427515183999994, 17.22311048, 38. 01770664, 33.35684888, 38.76923548, 9.694722036, 24.986610239999997, 40.67 908399999996, 36.349864196, 17.596806471999997, 17.165883972, 42.03045695 9999995, 41.053469468, 29.58541516, 30.647208199999998, 26.91714304, 67.69 964844, 29.58541516, 42.21661548, 51.732763231999996, 22.43554903999998, 38.500339839999995, 35.101223159999996, 11.85209244, 25.510612, 35.8527519 99999995, 40.56876784, 32.109882284729316, 33.70158688, 15.52010475999999 9, 37.2661778, 15.520104759999999, 19.98790924, 18.28490352, 30.44726016, 55.25460664, 10.222171176, 24.40055564, 65.69721314581203, 31.35047372]

In [90]:

```
#8.Design a method predicting the data point using the above two methods.
import numpy as np

def predict_knn(X_train, y_train, x_query, k):
    distances = []
    for i, x in enumerate(X_train):
        distance = euclidean_distance(x, x_query)
        distances.append((distance, y_train[i]))
    distances.sort()
    neighbors = [distances[i][1] for i in range(k)]
    counts = np.bincount(neighbors)
    return np.argmax(counts)

y_pred = []
for i, x in enumerate(X_test):
    y_pred.append(predict_knn_regression(X_train, y_train, x, 5))
print(y_pred)
```

[52.0659180352, 44.13887456799999, 64.33776346399999, 39.119489288, 12.211 171540799999, 38.695047862399996, 34.0528059544, 48.29917275199999, 25.524 401520000005, 38.827151464, 32.1717775312, 18.2195411952, 51.5783206079999 9, 49.266369684800004, 40.473620152, 32.8380871376, 32.9826013072, 20.5072 22563199996, 37.3780108072, 34.6116952, 31.55386914, 41.0927696, 41.295475 544, 24.337399638399997, 32.551540912, 34.175946368, 14.167352847999998, 3 7.6470443424, 50.528938136, 24.670830231999997, 36.8926197032, 29.15973267 7599997, 29.659602777599996, 47.150505736, 29.479235855999995, 35.25276998 48, 25.56577008, 40.1717675592, 13.775730479999998, 46.924357607999994, 1 8.469545192800002, 12.617410800000002, 35.1216316496, 39.771733584, 18.100 123951999997, 74.05661716, 42.76701432232481, 38.816119848, 20.830448912, 21.9890443824, 56.914864848, 40.57000889679999, 30.836124624, 26.174853178 399996, 65.49194628799998, 39.119489288, 18.124945087999997, 16.091818259 2, 36.220932184000006, 18.4079060384, 40.1717675592, 22.2316020392, 42.926 77576, 51.638994495999995, 22.887983191199996, 15.9664715224, 44.425834479 19999, 14.916951155200001, 32.097865704, 22.67686564, 16.6036852416, 14.45 85875104, 12.384367912, 32.1717775312, 29.214477072, 19.135716904, 51.8308 067192, 48.121287943999995, 48.10552849316241, 17.7847576296, 39.461745174 4, 46.478956112000006, 32.774241659999994, 31.652464207999998, 44.73706394 5600006, 39.119489288, 30.535513088, 35.501808716, 20.121667584, 20.383668 464, 28.074773244, 65.578820264, 17.038330912, 57.3157261944, 39.821375855 999996, 45.9520585528, 24.425376775999997, 23.926196152000003, 21.49827536 56, 35.545245703999996, 29.6455374672, 40.8994405296, 42.5670071832, 32.07 0700349599996, 66.357928144, 15.2385227616, 52.644250504, 33.6435330008, 3 6.62220721600001, 49.392819583199994, 43.30474650319999, 43.486630272, 29. 4061514, 42.45793207999999, 41.388062322324814, 52.4980815920000005, 25.983 592535999996, 33.70379320319999, 44.31262252, 39.821375855999996, 31.55386 914, 26.6152904472, 43.91134748799999, 29.912226783999994, 26.8390943568, 34.74269564, 50.476537959999995, 45.09862516, 43.6101843712, 38.6950478623 99996, 16.0918182592, 32.704604584, 15.272169190400001, 59.15704079999999, 15.7437707744, 43.424163746400005, 20.82906995999998, 42.860586064, 31.08 7093888000005, 32.83850082319999, 23.851456953599996, 35.113220042399995, 40.473620152, 31.117430831999997, 39.821375855999996, 39.290203545599994, 28.370006867199997, 14.916951155200001, 10.3209041392, 18.9576942008, 36.6 18070360000004, 12.211171540799999, 35.536971992, 21.987113849599996, 45.0 95867256, 40.312282768, 32.9826013072, 63.11463304, 44.13887456799999, 41. 65386516880001, 15.304160876800001, 49.618829816, 31.087093888000005, 51.1 6449711279999, 45.09862516, 50.11485855010827, 39.4265818984, 22.67686564, 32.209560816, 29.346856463999995, 40.109576824, 22.7434690216, 22.52104406 4, 37.0022463872, 30.2311783816, 16.672494946399997, 15.304160876800001, 4 2.601343088, 41.65386516880001, 33.42855438400001, 32.687919264799994, 22. 483674464799996, 49.392819583199994, 34.173188464000006, 29.12622414400000 2, 51.7131821136, 21.7962668928, 27.334965496000002, 35.699688328, 17.5375 11536, 35.536971992, 40.040629224, 41.347875720000005, 54.19261660705414, 35.407350504, 28.021683592, 41.15344348799999, 12.211171540799999, 25.0606 59962400003, 20.4640613656, 41.72708752, 52.49808159199999, 20.8639574456, 56.56598999199999, 54.19261660705414, 34.203525408000004]

In [87]:

```
#9.Choose any dataset from Kaggle or UCI repository suitable for regression and apply KNN
import pandas as pd
from sklearn.model_selection import train_test_split
import numpy as np
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/concrete/compressive/Con
df = pd.read_excel(url)
def euclidean_distance(x1, x2):
    return np.sqrt(np.sum((x1 - x2)**2))
def predict_knn_regression(X_train, y_train, x_query, k):
    distances = []
    for i, x in enumerate(X_train):
        distance = euclidean_distance(x, x_query)
        distances.append((distance, y_train[i]))
    distances.sort()
    neighbors = [distances[i][1] for i in range(k)]
    return np.mean(neighbors)
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
y_pred = []
for i, x in enumerate(X_test):
    y_pred.append(predict_knn_regression(X_train, y_train, x, k=5))
```

In [88]:

```
#10.Evaluate the designed regression model with appropriate metric
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)
print(f'Mean Absolute Error: {mae}')
print(f'Mean Squared Error: {mse}')
print(f'Root Mean Squared Error: {rmse}')
print(f'R-squared: {r2}')
```

Mean Absolute Error: 6.459309144164602 Mean Squared Error: 67.95464317359179 Root Mean Squared Error: 8.243460630923872 R-squared: 0.7362839326848325

•

In []:

In []:			

In []:

#Name: SIVAA V #Reg: 22MCA1127 #Lab Exercise: 8

In [1]:

```
#Load the dataset (titanic).
import pandas as pd
data = pd.read_csv("C:/Users/student/Downloads/titanic/train.csv")
print(data)
     PassengerId
                  Survived
                              Pclass
                                       \
0
                                    3
                1
                           0
1
                2
                           1
                                    1
2
                3
                                    3
                           1
3
                4
                           1
                                    1
4
                5
                           0
                                    3
                         . . .
. .
              887
                           0
                                    2
886
887
              888
                           1
                                    1
                                    3
888
              889
                           0
889
              890
                           1
                                    1
              891
                           0
                                    3
890
                                                                       Age SibS
                                                      Name
                                                                Sex
   \
p
                                 Braund, Mr. Owen Harris
                                                                     22.0
0
                                                               male
1
1
     Cumings, Mrs. John Bradley (Florence Briggs Th...
                                                            female
                                                                     38.0
1
2
                                  Heikkinen, Miss. Laina
                                                            female
                                                                     26.0
0
3
          Futrelle, Mrs. Jacques Heath (Lily May Peel)
                                                             female
                                                                     35.0
1
4
                                Allen, Mr. William Henry
                                                               male
                                                                    35.0
0
. .
. . .
886
                                   Montvila, Rev. Juozas
                                                               male 27.0
0
887
                            Graham, Miss. Margaret Edith female
                                                                     19.0
0
               Johnston, Miss. Catherine Helen "Carrie"
                                                             female
                                                                      NaN
888
1
                                    Behr, Mr. Karl Howell
889
                                                               male
                                                                     26.0
0
890
                                      Dooley, Mr. Patrick
                                                               male 32.0
0
     Parch
                        Ticket
                                    Fare Cabin Embarked
0
         0
                    A/5 21171
                                 7.2500
                                           NaN
                                                       S
                                                       C
1
         0
                     PC 17599
                                71.2833
                                           C85
                                                       S
2
         0
            STON/02. 3101282
                                 7.9250
                                           NaN
                                                       S
3
         0
                        113803
                                53.1000
                                          C123
                                                       S
4
         0
                        373450
                                 8.0500
                                           NaN
                                           . . .
                                                     . . .
. .
        . . .
                                13.0000
                                                       S
886
         0
                        211536
                                           NaN
                                                       S
         0
                        112053
                                30.0000
887
                                           B42
                   W./C. 6607
                                                       S
888
         2
                                23.4500
                                           NaN
                                                       C
         0
                                30.0000
                                          C148
889
                        111369
```

[891 rows x 12 columns]

370376

7.7500

NaN

Q

0

```
In [17]:
#2.Split dataset into test and train (20:80)
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(data, data, test_size=0.2, random_sta
X_train = X_train.drop(['Pclass','Name','Sex','Age','SibSp','Parch','Ticket','Fare','Cabi
X_test = X_test.drop(['Pclass','Name','Sex','Age','SibSp','Parch','Ticket','Fare','Cabin'
y_train = y_train.drop(['Pclass','Name','Sex','Age','SibSp','Parch','Ticket','Fare','Cabi
y_test = y_test.drop(['Pclass','Name','Sex','Age','SibSp','Parch','Ticket','Fare','Cabin'
print(y_train)
     Survived
140
439
            0
817
            0
            0
378
491
            0
835
            1
192
            1
629
            0
559
            1
            0
684
[712 rows x 1 columns]
```

In [18]:

```
#3.Build KNN classifier with k value as 2 for identifying the Passenger Survive
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=2)
knn.fit(X_train, y_train.values.reshape(-1,))
y_pred_2 = knn.predict(X_test)
```

In [20]:

```
#4.Build KNN classifier with k value as 4 for identifying the the Passenger Survived.
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=4)
knn.fit(X_train, y_train.values.reshape(-1,))
y_pred_4 = knn.predict(X_test)
```

```
In [22]:
```

```
#5. Evaluate the step-3 and step-4.
print("Predicted values for Step-3")
print(X_test)
print(y_pred_2)
print(X_test)
print("\nPredicted values for Step-4")
print(y_pred_4)
Predicted values for Step-3
  PassengerId
495
      496
      649
648
278
      279
31
       32
      256
255
       . . .
. .
780
      781
837
      838
215
      216
833
      834
372
      373
[179 rows x 1 columns]
[0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0
PassengerId
495
      496
648
      649
      279
278
31
       32
255
      256
       . . .
      781
780
      838
837
215
      216
      834
833
372
      373
[179 rows x 1 columns]
Predicted values for Step-4
```

```
In [25]:
#6.Design a method for calculating the distance between data points for the given dataset
import numpy as np
def euclidean distance(x1, y1):
   return np.sqrt(np.sum((x1 - y1)**2))
d = euclidean_distance(X_test,y_test)
print(d)
PassengerId
            0.0
Survived
            0.0
dtype: float64
In [27]:
#7. Design a method for finding the nearest neighbours of a given data point using the ab
import numpy as np
def find_nearest_neighbor(X, y, x_query):
   distances = []
   for i, x in enumerate(X):
      distance = euclidean_distance(x, x_query)
      distances.append((distance, y[i]))
   distances.sort()
   return distances[0][1]
In [33]:
#8.Design a method predicting the data point using the above two methods.
import numpy as np
import pandas as pd
def predict_knn_regression(X_train, y_train, x_query, k):
   distances = []
   for i, x in enumerate(X_train):
      distance = euclidean_distance(x, x_query)
      distances.append((distance, y_train[i]))
   distances.sort()
   neighbors = [distances[i][1] for i in range(k)]
   return np.mean(neighbors)
y_pred = []
for i, x in enumerate(X_test):
   y_pred.append(predict_knn_regression(X_train, y_train, x, k=5))
```

In []:			

In []:

```
#Name: SIVAA V
#Reg: 22MCA1127
#Lab Exercise: 9
```

In [1]:

```
#1.Load the dataset (iris.csv)
import pandas as pd
data = pd.read_csv("Iris.csv")
print(data)
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	\
0	1	5.1	3.5	1.4	0.2	
1	2	4.9	3.0	1.4	0.2	
2	3	4.7	3.2	1.3	0.2	
3	4	4.6	3.1	1.5	0.2	
4	5	5.0	3.6	1.4	0.2	
• •	• • •	• • •			• • •	
145	146	6.7	3.0	5.2	2.3	
146	147	6.3	2.5	5.0	1.9	
147	148	6.5	3.0	5.2	2.0	
148	149	6.2	3.4	5.4	2.3	
149	150	5.9	3.0	5.1	1.8	

Species

Iris-setosa

1 Iris-setosa
2 Iris-setosa
3 Iris-setosa
4 Iris-setosa
.......
145 Iris-virginica
146 Iris-virginica
147 Iris-virginica
148 Iris-virginica

0

149

[150 rows x 6 columns]

Iris-virginica

In [2]:

```
#2.Load the dataset (Churnprediction.csv)
```

import pandas as pd
train_data = pd.read_csv("C:/users/student/Machine Learning/customer-churn-prediction-202
print(train_data)

		account_lengt	h	area_code	international_pla	an voic	e_mail_pl
an \ 0	ОН	10	7	area_code_415	1	no	у
es 1	NJ	13	7	area_code_415	1	10	
no 2	ОН	8	4	area_code_408	ye	es	
no 3	OK	7	5	area_code_415	ye	es.	
no 4	MA	12	1	area_code_510	1	10	у
es ···		••		•••		• •	
4245	МТ	8	3	area_code_415	1	10	
no 4246	WV	7	3	area_code_408	1	10	
no 4247	NC	7	5	area_code_408	1	10	
no 4248	HI	5	0	area_code_408	1	10	У
es 4249 es	VT	8	6	area_code_415	,	10	у
0 1 2 3 4 4245 4246 4247 4248 4249	numbe		es 26 0 0 24 0 0 40 34	2 2 3 3 1 1 2	nutes total_day_0 161.6 243.4 299.4 166.7 218.2 188.3 177.9 170.7 235.7	71 113 88 70 89 101 127	\
	total				total_eve_calls		_eve_char
ge \ 0		27.47		195.5	103		16.
62 1		41.38		121.2	110		10.
30 2		50.90		61.9	88		5.
26 3		28.34		148.3	122		12.
61 4 62		37.09		348.5	108		29.
•••					•••		
4245		32.01		243.8	88		20.
72 4246 15		30.24		131.2	82		11.
4247		29.02		193.1	126		16.
41 4248		40.07		223.0	126		18.
96 4249		22.00		267.1	104		22.

0 1 2 3 4	total_night_minutes 254.4 162.6 196.9 186.9 212.6 	10 10 8 12 11	4 7.32 9 8.86 1 8.41 8 9.57	\
4245 4246	213.7 186.2	7 8		
4247	129.1	10		
4248	297.5	11		
4249	154.8	10		
0 1 2 3	total_intl_minutes 13.7 12.2 6.6 10.1	total_intl_calls 3 5 7 3 7	total_intl_charge \ 3.70 3.29 1.78 2.73	
4	7.5	,,,	2.03	
4245	10.3	6	2.78	
4246	11.5	6	3.11	
4247	6.9	7	1.86	
4248	9.9	5	2.67	
4249	9.3	16	2.51	
	number_customer_ser	vice_calls churn		
0		1 no		
1		0 no		
2 3		2 no		
3 4		3 no 3 no		
4				
4245		0 no		
4246		3 no		
4247		1 no		
4248		2 no		
4249		0 no		

[4250 rows x 20 columns]

In [7]:

```
#3.Drop columns that are not required for classification of Churn Risk.
train_data.drop(columns=['state', 'area_code'],axis=1,inplace=True)
train_data.drop(columns=['total_day_minutes', 'total_eve_minutes', 'total_night_minutes',
print(train_data)
```

```
account_length international_plan voice_mail_plan
0
                   107
                                                            yes
1
                   137
                                           no
                                                             no
2
                    84
                                         yes
                                                             no
3
                    75
                                         yes
                                                             no
4
                   121
                                           no
                                                            yes
                    . . .
. . .
                                          . . .
                                                            . . .
                    83
4245
                                                             no
                                           no
                    73
4246
                                           no
                                                             no
4247
                     75
                                           no
                                                             no
4248
                     50
                                           no
                                                            yes
4249
                    86
                                           no
                                                            yes
                                 total_day_calls
                                                    total_day_charge
      number_vmail_messages
0
                                                                  27.47
                             26
                                               123
                              0
1
                                               114
                                                                  41.38
2
                              0
                                                71
                                                                  50.90
3
                              0
                                                                  28.34
                                               113
4
                             24
                                                88
                                                                  37.09
                                                                    . . .
4245
                              0
                                                70
                                                                  32.01
4246
                              0
                                                89
                                                                  30.24
4247
                              0
                                               101
                                                                  29.02
4248
                             40
                                               127
                                                                  40.07
4249
                             34
                                               102
                                                                  22.00
                          total_eve_charge
                                              total_night_calls
      total_eve_calls
0
                     103
                                       16.62
                                                                103
                                                                104
1
                     110
                                       10.30
2
                     88
                                        5.26
                                                                 89
3
                     122
                                       12.61
                                                                121
4
                     108
                                       29.62
                                                                118
                     . . .
                                                                . . .
                                          . . .
. . .
                                                                79
4245
                     88
                                       20.72
4246
                     82
                                       11.15
                                                                89
4247
                     126
                                       16.41
                                                                104
4248
                     126
                                       18.96
                                                                116
4249
                     104
                                       22.70
                                                                100
      total_night_charge
                             total_intl_calls
                                                  total_intl_charge
0
                      11.45
                                               3
                                                                  3.70
                                               5
1
                       7.32
                                                                  3.29
                                               7
2
                       8.86
                                                                  1.78
                                               3
3
                       8.41
                                                                  2.73
4
                       9.57
                                               7
                                                                  2.03
                        . . .
                                              . . .
                                                                   . . .
4245
                       9.62
                                               6
                                                                  2.78
4246
                       8.38
                                               6
                                                                  3.11
                                               7
4247
                       5.81
                                                                  1.86
4248
                      13.39
                                               5
                                                                  2.67
4249
                       6.97
                                              16
                                                                  2.51
      number_customer_service_calls churn
0
                                       1
                                             no
                                       0
1
                                             no
                                       2
2
                                             no
                                       3
3
                                             no
                                       3
4
                                             no
                                     . . .
                                            . . .
. . .
4245
                                       0
                                             no
4246
                                       3
                                             no
```

In [8]:

```
#4.If require perform data preprocessing.
train_data['international_plan'].replace({'yes':1,'no':0},inplace=True)
train_data['voice_mail_plan'].replace({'yes':1,'no':0},inplace=True)
train_data['churn'].replace({'yes':1,'no':0},inplace=True)
```

In [23]:

```
#5.Split dataset into test and train (20:80)
X = train_data.drop("churn", axis=1)
y = train_data["churn"]

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
```

In [13]:

```
#6.Build any three classification models for identifying Churn Risk.

#Random Forest
X = train_data.drop("churn", axis=1)
y = train_data["churn"]

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = from sklearn.preprocessing import StandardScaler
st_x= StandardScaler()
x_train= st_x.fit_transform(X_train)
x_test= st_x.transform(X_test)

from sklearn.ensemble import RandomForestClassifier
classifier= RandomForestClassifier(n_estimators= 10, criterion="entropy")
classifier.fit(x_train, y_train)
y_pred= classifier.predict(x_test)
print(y_pred)
```

 $0\; 1\; 0\; 0\; 0\; 1\; 0\; 0\; 0\; 0\; 0\; 0\; 0\; 0\; 0\; 0\; 0\; 0\; 1\; 1\; 0\; 0\; 0\; 0\; 0\; 0\; 0\; 0\; 1\; 0\; 0\; 1\; 0\; 0\; 0$

In [20]:

```
#Naive Bayes
from sklearn.naive_bayes import GaussianNB
from sklearn.preprocessing import StandardScaler
X = train_data.drop("churn", axis=1)
y = train_data["churn"]

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = sc = StandardScaler()
x_train = sc.fit_transform(X_train)
x_test = sc.transform(X_test)

model = GaussianNB()
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
print(y_pred)
```

In [22]:

```
#Logistic Regression
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
X = train_data.drop("churn", axis=1)
y = train_data["churn"]

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = st_x = StandardScaler()
x_train= st_x.fit_transform(X_train)
x_test= st_x.transform(X_test)

classifier = LogisticRegression(random_state=0)
classifier.fit(x_train, y_train)
y_pred = classifier.predict(x_test)
print(y_pred)
```

c-regression)

n_iter_i = _check_optimize_result(

```
#7.Build Voting ensemble classifier on the training dataset.
from sklearn.ensemble import VotingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
X = train data.drop("churn", axis=1)
y = train_data["churn"]
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
classifier1 = DecisionTreeClassifier()
classifier2 = LogisticRegression()
classifier3 = SVC()
voting_classifier = VotingClassifier(
    estimators=[('dt', classifier1), ('lr', classifier2), ('svc', classifier3)],
    voting='hard'
)
voting_classifier.fit(X_train, y_train)
y_pred = voting_classifier.predict(X_test)
/home/sivaa/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_lo
gistic.py:814: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
Increase the number of iterations (max_iter) or scale the data as shown i
n:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://sc
ikit-learn.org/stable/modules/preprocessing.html)
```

Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-reg ression (https://scikit-learn.org/stable/modules/linear_model.html#logisti

In [31]:

```
#8.Build Bagging ensemble classifier on the training dataset.
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
X = train_data.drop("churn", axis=1)
y = train_data["churn"]
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
base_classifier = DecisionTreeClassifier()
bagging_classifier = BaggingClassifier(
    base_estimator=base_classifier,
    n_estimators=10,
    random_state=42
)
bagging_classifier.fit(X_train, y_train)
y_pred = bagging_classifier.predict(X_test)
```

In [32]:

In []:

```
#10. Fit the models designed from step-5 to step-8 on the test dataset.
#Random Forest
X = train_data.drop("churn", axis=1)
y = train_data["churn"]
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
from sklearn.preprocessing import StandardScaler
st x= StandardScaler()
x_train= st_x.fit_transform(X_train)
x_test= st_x.transform(X_test)
from sklearn.ensemble import RandomForestClassifier
classifier= RandomForestClassifier(n_estimators= 10, criterion="entropy")
classifier.fit(x_test, y_test)
y_pred= classifier.predict(x_train)
print(y_pred)
#Naive Bayes
from sklearn.naive_bayes import GaussianNB
x_train = sc.fit_transform(X_train)
x_test = sc.transform(X_test)
model = GaussianNB()
model.fit(x_test, y_test)
y_pred = model.predict(x_train)
#Logistic Regression
classifier = LogisticRegression(random_state=0)
classifier.fit(x_test, y_test)
y_pred = classifier.predict(x_train)
print(y_pred)
```

```
#11.Evaluate the designed models from step-5 to step-8 with appropriate classifi
X = train_data.drop("churn", axis=1)
y = train_data["churn"]
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
from sklearn.preprocessing import StandardScaler
st_x= StandardScaler()
x_train= st_x.fit_transform(X_train)
x_test= st_x.transform(X_test)
from sklearn.ensemble import RandomForestClassifier
classifier= RandomForestClassifier(n_estimators= 10, criterion="entropy")
classifier.fit(x_train, y_train)
y_pred= classifier.predict(x_test)
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test, y_pred)
print("Random Forest Accuracy: ",accuracy)
from sklearn.metrics import precision_score
precision = precision_score(y_test, y_pred)
print("Random Forest Precision: ",precision)
from sklearn.metrics import recall score
recall = recall_score(y_test, y_pred)
print("Random Forest Recall: ",recall)
from sklearn.metrics import f1_score
f1 = f1_score(y_test, y_pred)
print("Random Forest F1 score: ",f1)
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
from sklearn.metrics import classification report
report = classification_report(y_test, y_pred)
print("Random Forest Classification")
print(report)
#Naive Bayes
from sklearn.naive bayes import GaussianNB
x train = sc.fit transform(X train)
x_test = sc.transform(X_test)
model = GaussianNB()
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
from sklearn.metrics import accuracy_score
accuracy = accuracy score(y test, y pred)
print("Naive Bayes Accuracy: ",accuracy)
from sklearn.metrics import precision_score
precision = precision_score(y_test, y_pred)
```

```
print("Naive Bayes Precision: ",precision)
from sklearn.metrics import recall score
recall = recall_score(y_test, y_pred)
print("Naive Bayes Recall: ",recall)
from sklearn.metrics import f1_score
f1 = f1_score(y_test, y_pred)
print("Naive Bayes F1 score: ",f1)
from sklearn.metrics import confusion matrix
cm = confusion_matrix(y_test, y_pred)
from sklearn.metrics import classification_report
report = classification_report(y_test, y_pred)
print("Naive Bayes Classification")
print(report)
#Logistic Regression
classifier = LogisticRegression(random_state=0)
classifier.fit(x_train, y_train)
y_pred = classifier.predict(x_test)
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test, y_pred)
print("Logistic Regression Accuracy: ",accuracy)
from sklearn.metrics import precision_score
precision = precision_score(y_test, y_pred)
print("Logistic Regression Precision: ",precision)
from sklearn.metrics import recall_score
recall = recall_score(y_test, y_pred)
print("Logistic Regression Recall: ",recall)
from sklearn.metrics import f1_score
f1 = f1_score(y_test, y_pred)
print("Logistic Regression F1 score: ",f1)
from sklearn.metrics import confusion matrix
cm = confusion_matrix(y_test, y_pred)
from sklearn.metrics import classification_report
report = classification_report(y_test, y_pred)
print("Logistic Regression Classification")
print(report)
```

Random Forest Accuracy: 0.9423529411764706 Random Forest Precision: 0.9294117647058824 Random Forest Recall: 0.6475409836065574 Random Forest F1 score: 0.7632850241545894

Random Forest Classification

	precision	recall	f1-score	support
0	0.94	0.99	0.97	728
1	0.93	0.65	0.76	122
accuracy			0.94	850
macro avg	0.94	0.82	0.87	850
weighted avg	0.94	0.94	0.94	850

Naive Bayes Accuracy: 0.8470588235294118
Naive Bayes Precision: 0.46296296296296297
Naive Bayes Recall: 0.4098360655737705
Naive Bayes F1 score: 0.43478260869565216

Naive Bayes Classification

	precision	recall	f1-score	support
0	0.90	0.92	0.91	728
1	0.46	0.41	0.43	122
accuracy			0.85	850
macro avg	0.68	0.67	0.67	850
weighted avg	0.84	0.85	0.84	850

Logistic Regression Accuracy: 0.8623529411764705 Logistic Regression Precision: 0.5609756097560976 Logistic Regression Recall: 0.1885245901639344 Logistic Regression F1 score: 0.2822085889570552

Logistic Regression Classification

	precision	recall	f1-score	support
0	0.88	0.98	0.92	728
1	0.56	0.19	0.28	122
accuracy			0.86	850
macro avg	0.72	0.58	0.60	850
weighted avg	0.83	0.86	0.83	850

In []:

In []:

```
#Name: SIVAA V
#Reg: 22MCA1127
#Lab Exercise: 10
```

In [1]:

```
#1.Load the dataset (iris.csv).
import pandas as pd
data = pd.read_csv("C:/Users/student/Downloads/archive (2)/pima-indians-diabetes.csv")
print(data)
     6
        148
             72
                 35
                       0 33.6 0.627
                                       50
                                          1
0
     1
         85
             66
                 29
                       0
                          26.6
                               0.351
                                       31
                                           0
1
       183
             64
                         23.3 0.672 32
                                          1
     8
                 0
                       0
2
     1
        89
             66
                 23
                      94
                          28.1 0.167
                                       21
                                          0
     0 137
                                2.288
3
             40
                 35
                     168
                         43.1
                                       33
                                           1
```

25.6 0.201 30 0 10 101 76 32.9 0.171 36.8 0.340 2 122 5 121 26.2 0.245 30 0 1 126 60 30.1 0.349 47 1 93 70 0 30.4 0.315 23 0

[767 rows x 9 columns]

In [2]:

#2.check if there are missing values are present in the dataset.
data.isnull()

Out[2]:

	6	148	72	35	0	33.6	0.627	50	1
0	False								
1	False								
2	False								
3	False								
4	False								
762	False								
763	False								
764	False								
765	False								
766	False								

767 rows × 9 columns

In [5]:

```
#3. Perform data preprocessing.
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age',
'class']
data=pd.read_csv("C:/Users/student/Downloads/archive (2)/pima-indians-diabetes.csv",names
print(data)
```

```
preg plas
                 pres
                       skin
                             test
                                           pedi
                                                      class
                                    mass
                                                 age
0
            148
                   72
                         35
                                    33.6
                                          0.627
        6
                                 0
                                                  50
                                                           1
             85
                         29
1
        1
                   66
                                 0
                                   26.6 0.351
                                                  31
                                                           0
2
        8
            183
                   64
                          0
                                 0
                                    23.3
                                         0.672
                                                  32
                                                           1
3
        1
             89
                   66
                         23
                               94
                                    28.1 0.167
                                                  21
                                                           0
4
        0
            137
                   40
                         35
                               168
                                    43.1 2.288
                                                  33
                                                           1
                   . . .
                         . . .
      . . .
            ...
                               . . .
                                     . . .
                                    32.9
763
       10
            101
                   76
                         48
                               180
                                          0.171
                                                  63
                                                           0
        2
764
            122
                   70
                         27
                               0 36.8 0.340
                                                  27
                                                           0
765
        5
            121
                   72
                          23
                               112 26.2 0.245
                                                  30
                                                           0
        1
            126
                          0
                                 0 30.1 0.349
                                                  47
766
                   60
                                                           1
767
        1
             93
                   70
                         31
                                 0 30.4 0.315
                                                  23
                                                           0
```

[768 rows x 9 columns]

In [6]:

```
#4.Split dataset into test and train (20:80).
from sklearn.model_selection import train_test_split

X=data.iloc[:,:-1]
y=data.iloc[:, -1:]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
```

().

classifier.fit(x_train, y_train)

```
#5.Build any three classification models for identifying diabetes.
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
from sklearn.preprocessing import StandardScaler
st_x= StandardScaler()
x_train= st_x.fit_transform(X_train)
x_test= st_x.transform(X_test)
from sklearn.ensemble import RandomForestClassifier
classifier= RandomForestClassifier(n_estimators= 10, criterion="entropy")
classifier.fit(x_train, y_train)
y_pred= classifier.predict(x_test)
print(y_pred)
0 0 1 0 0 0]
```

C:\Users\student\AppData\Local\Temp/ipykernel_1976/2771513193.py:12: DataC onversionWarning: A column-vector y was passed when a 1d array was expecte d. Please change the shape of y to (n_samples,), for example using ravel

In [8]:

```
#Naive Bayes
from sklearn.naive_bayes import GaussianNB
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age',
data=pd.read_csv("C:/Users/student/Downloads/archive (2)/pima-indians-diabetes.csv",names
X=data.iloc[:,:-1]
y=data.iloc[:, -1:]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
sc = StandardScaler()
x_train = sc.fit_transform(X_train)
x_test = sc.transform(X_test)
model = GaussianNB()
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
print(y_pred)
```

1 0 1 0 0 0]

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed when a 1d array was ex pected. Please change the shape of y to (n_samples,), for example using r avel().

return f(*args, **kwargs)

In [10]:

return f(*args, **kwargs)

1 0 1 0 0 0]

```
#Logistic Regression
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age',
'class']
data=pd.read_csv("C:/Users/student/Downloads/archive (2)/pima-indians-diabetes.csv",names
X=data.iloc[:,:-1]
y=data.iloc[:, -1:]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
sc = StandardScaler()
x_train = sc.fit_transform(X_train)
x_test = sc.transform(X_test)
classifier = LogisticRegression(random_state=0)
classifier.fit(x_train, y_train)
y_pred = classifier.predict(x_test)
print(y_pred)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:63:
DataConversionWarning: A column-vector y was passed when a 1d array was ex
pected. Please change the shape of y to (n_samples, ), for example using r
avel().
```

```
#6.Build Voting ensemble classifier on the training dataset.
from sklearn.ensemble import VotingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear model import LogisticRegression
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age',
'class']
data=pd.read_csv("C:/Users/student/Downloads/archive (2)/pima-indians-diabetes.csv",names
X=data.iloc[:,:-1]
y=data.iloc[:, -1:]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
classifier1 = DecisionTreeClassifier()
classifier2 = LogisticRegression(solver='lbfgs',max_iter=100)
classifier3 = SVC()
voting_classifier = VotingClassifier(
   estimators=[('dt', classifier1), ('lr', classifier2), ('svc', classifier3)],
   voting='hard'
)
voting_classifier.fit(X_train, y_train)
y_pred = voting_classifier.predict(X_test)
print(y_pred)
101000]
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:63:
DataConversionWarning: A column-vector y was passed when a 1d array was ex
pected. Please change the shape of y to (n_samples, ), for example using r
avel().
  return f(*args, **kwargs)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.
py:763: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
Increase the number of iterations (max_iter) or scale the data as shown i
   https://scikit-learn.org/stable/modules/preprocessing.html (https://sc
ikit-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
   https://scikit-learn.org/stable/modules/linear model.html#logistic-reg
ression (https://scikit-learn.org/stable/modules/linear model.html#logisti
c-regression)
  n_iter_i = _check_optimize_result(
```

avel().

return f(*args, **kwargs)

```
#7.Build Bagging ensemble classifier on the training dataset.
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model selection import train test split
from sklearn.metrics import accuracy_score
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age',
data=pd.read_csv("C:/Users/student/Downloads/archive (2)/pima-indians-diabetes.csv",names
X=data.iloc[:,:-1]
y=data.iloc[:, -1:]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
base_classifier = DecisionTreeClassifier()
bagging_classifier = BaggingClassifier(
   base_estimator=base_classifier,
   n_estimators=10,
   random_state=42
)
bagging_classifier.fit(X_train, y_train)
y_pred = bagging_classifier.predict(X_test)
print(y_pred)
1 0 0 0 0 0]
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:63:
DataConversionWarning: A column-vector y was passed when a 1d array was ex
```

pected. Please change the shape of y to (n_samples,), for example using r

```
In [20]:
```

return f(*args, **kwargs)

1 0 1 0 0 0]

```
#8.Build Boosting ensemble classifier on the training dataset.
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age',
'class']
data=pd.read_csv("C:/Users/student/Downloads/archive (2)/pima-indians-diabetes.csv",names
X=data.iloc[:,:-1]
y=data.iloc[:, -1:]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
boosting_classifier = GradientBoostingClassifier(
    n_estimators=100,
    learning_rate=0.1
)
boosting_classifier.fit(X_train, y_train)
y_pred = boosting_classifier.predict(X_test)
print(y_pred)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:63:
DataConversionWarning: A column-vector y was passed when a 1d array was ex
pected. Please change the shape of y to (n_samples, ), for example using r
avel().
```

```
#9.Fit the models designed from step-5 to step-8 on the test dataset.
from sklearn.model selection import train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
from sklearn.preprocessing import StandardScaler
st_x= StandardScaler()
x_train= st_x.fit_transform(X_train)
x_test= st_x.transform(X_test)
from sklearn.ensemble import RandomForestClassifier
classifier= RandomForestClassifier(n_estimators= 10, criterion="entropy")
classifier.fit(x_test, y_test)
y_pred= classifier.predict(x_train)
print("Random Forest")
print(y_pred)
#Naive Bayes
from sklearn.naive_bayes import GaussianNB
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age',
'class']
data=pd.read_csv("C:/Users/student/Downloads/archive (2)/pima-indians-diabetes.csv",names
X=data.iloc[:,:-1]
y=data.iloc[:, -1:]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
sc = StandardScaler()
x_train = sc.fit_transform(X_train)
x_test = sc.transform(X_test)
model = GaussianNB()
model.fit(x_test, y_test)
y_pred = model.predict(x_train)
print("Naive Bayes")
print(y_pred)
#Logistic Regression
from sklearn.linear_model import LogisticRegression
from sklearn.model selection import train test split
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age',
'class']
data=pd.read_csv("C:/Users/student/Downloads/archive (2)/pima-indians-diabetes.csv",names
X=data.iloc[:,:-1]
y=data.iloc[:, -1:]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
sc = StandardScaler()
x_train = sc.fit_transform(X_train)
x_test = sc.transform(X_test)
classifier = LogisticRegression(random state=0)
classifier.fit(x_test, y_test)
y_pred = classifier.predict(x_train)
print("Logistic Regression")
```

Randomy-Bredt

1 1 0 0 0 1 0 0 0 0 0 0 0 1 1 1 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1 1 0 0 0 1

Naive Bayes

0 0 0 0 1 0 0 1 0 1 0 1 0 0 0 1 0 0 1 0 0 0]

Logistic Regression

1000001000010000100001011010000001000010 0 0 0 0 1 0 0 1 0 0 1 1 0 0 0 1 0 0 1 0 0 0]

C:\Users\student\AppData\Local\Temp/ipykernel_1976/3890763543.py:10: DataC onversionWarning: A column-vector y was passed when a 1d array was expecte d. Please change the shape of y to (n_samples,), for example using ravel ().

classifier.fit(x_test, y_test)

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed when a 1d array was ex pected. Please change the shape of y to (n_samples,), for example using r avel().

return f(*args, **kwargs)

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed when a 1d array was ex pected. Please change the shape of y to (n_samples,), for example using r avel().

return f(*args, **kwargs)

```
#10.Evaluate the designed models from step-5 to step-8 with appropriate classifi
import pandas as pd
from sklearn.model_selection import train_test_split
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age',
'class']
data=pd.read_csv("C:/Users/student/Downloads/archive (2)/pima-indians-diabetes.csv",names
X=data.iloc[:,:-1]
y=data.iloc[:, -1:]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state =
from sklearn.preprocessing import StandardScaler
st_x= StandardScaler()
x_train= st_x.fit_transform(X_train)
x_test= st_x.transform(X_test)
from sklearn.ensemble import RandomForestClassifier
classifier= RandomForestClassifier(n_estimators= 10, criterion="entropy")
classifier.fit(x_train, y_train)
y_pred= classifier.predict(x_test)
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test, y_pred)
print("Random Forest Accuracy: ",accuracy)
from sklearn.metrics import precision_score
precision = precision_score(y_test, y_pred)
print("Random Forest Precision: ",precision)
from sklearn.metrics import recall_score
recall = recall_score(y_test, y_pred)
print("Random Forest Recall: '
                              ',recall)
from sklearn.metrics import f1_score
f1 = f1_score(y_test, y_pred)
print("Random Forest F1 score: ",f1)
from sklearn.metrics import confusion matrix
cm = confusion_matrix(y_test, y_pred)
from sklearn.metrics import classification report
report = classification_report(y_test, y_pred)
print("Random Forest Classification")
print(report)
#Naive Bayes
from sklearn.naive_bayes import GaussianNB
x_train = sc.fit_transform(X_train)
x_test = sc.transform(X_test)
model = GaussianNB()
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
from sklearn.metrics import accuracy score
```

```
accuracy = accuracy_score(y_test, y_pred)
print("Naive Bayes Accuracy: ",accuracy)
from sklearn.metrics import precision score
precision = precision_score(y_test, y_pred)
print("Naive Bayes Precision: ",precision)
from sklearn.metrics import recall_score
recall = recall_score(y_test, y_pred)
print("Naive Bayes Recall: ",recall)
from sklearn.metrics import f1_score
f1 = f1_score(y_test, y_pred)
print("Naive Bayes F1 score: ",f1)
from sklearn.metrics import confusion matrix
cm = confusion_matrix(y_test, y_pred)
from sklearn.metrics import classification_report
report = classification_report(y_test, y_pred)
print("Naive Bayes Classification")
print(report)
#Logistic Regression
classifier = LogisticRegression(random_state=0)
classifier.fit(x_train, y_train)
y_pred = classifier.predict(x_test)
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test, y_pred)
print("Logistic Regression Accuracy: ",accuracy)
from sklearn.metrics import precision score
precision = precision_score(y_test, y_pred)
print("Logistic Regression Precision: ",precision)
from sklearn.metrics import recall_score
recall = recall_score(y_test, y_pred)
print("Logistic Regression Recall: ",recall)
from sklearn.metrics import f1 score
f1 = f1_score(y_test, y_pred)
print("Logistic Regression F1 score: ",f1)
from sklearn.metrics import confusion matrix
cm = confusion_matrix(y_test, y_pred)
from sklearn.metrics import classification_report
report = classification_report(y_test, y_pred)
print("Logistic Regression Classification")
print(report)
C:\Users\student\AppData\Local\Temp/ipykernel_1976/3442923170.py:19: DataC
onversionWarning: A column-vector y was passed when a 1d array was expecte
d. Please change the shape of y to (n_samples,), for example using ravel
```

classifier.fit(x_train, y_train)

Random Forest Accuracy: 0.8116883116883117
Random Forest Precision: 0.7631578947368421
Random Forest Recall: 0.5918367346938775
Random Forest F1 score: 0.6666666666666667

Random Forest Classification

	precision	recall	f1-score	support
0	0.83	0.91	0.87	105
1	0.76	0.59	0.67	49
accuracy			0.81	154
macro avg	0.80	0.75	0.77	154
weighted avg	0.81	0.81	0.80	154

Naive Bayes Accuracy: 0.8051948051948052 Naive Bayes Precision: 0.7021276595744681 Naive Bayes Recall: 0.673469387755102 Naive Bayes F1 score: 0.6875000000000001

Naive Bayes Classification

	precision	recall f1-score		support
0	0.85	0.87	0.86	105
1	0.70	0.67	0.69	49
accuracy			0.81	154
macro avg	0.78	0.77	0.77	154
weighted avg	0.80	0.81	0.80	154

Logistic Regression Accuracy: 0.8051948051948052 Logistic Regression Precision: 0.7209302325581395 Logistic Regression Recall: 0.6326530612244898 Logistic Regression F1 score: 0.6739130434782609

Logistic Regression Classification

support	f1-score	recision recall		
105	0.86	0.89	0.84	0
49	0.67	0.63	0.72	1
154	0.81			accuracy
154	0.77	0.76	0.78	macro avg
154	0.80	0.81	0.80	weighted avg

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed when a 1d array was ex pected. Please change the shape of y to (n_samples,), for example using r avel().

return f(*args, **kwargs)

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y was passed when a 1d array was expected: Please change the shape of y to (n_samples,), for example using r avel().

return f(*args, **kwargs)

In []:

```
#Name: SIVAA V
#Reg: 22MCA1127
#Lab Exercise: 11
```

In [3]:

```
#1.Load the dataset (Mall Customers.csv)
import pandas as pd
data = pd.read_csv("Mall_Customers.csv")
print(data)
```

	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40
	• • •			• • •	•••
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

[200 rows x 5 columns]

In [4]:

```
#2. If require perform data preprocessing.
data.isnull().sum()
```

Out[4]:

CustomerID 0
Gender 0
Age 0
Annual Income (k\$) 0
Spending Score (1-100) 0

dtype: int64

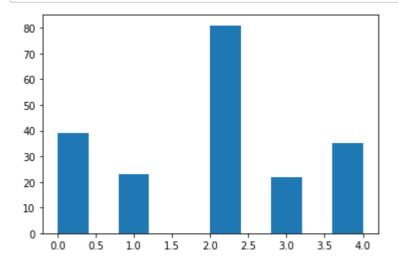
```
In [5]:
```

```
#3. Perform k-means clustering using sklearn with arbitrary number of clusters
 from sklearn.cluster import KMeans
 import numpy as np
X= data.iloc[:, [3,4]].values
n_{clusters} = 5
 kmeans = KMeans(n_clusters=n_clusters)
 kmeans.fit(X)
 labels = kmeans.labels_
 centers = kmeans.cluster_centers_
 print("Cluster Labels:")
 print(labels)
 print("Cluster Centers:")
 print(centers)
 Cluster Labels:
 [1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\ 3\ 1\
```

In [6]:

```
#4.Draw the inferences you find out from the clustering process.
```

```
import matplotlib.pyplot as plt
plt.hist(labels)
plt.show()
```



In [7]:

```
from sklearn.cluster import KMeans
import numpy as np
import matplotlib.pyplot as plt

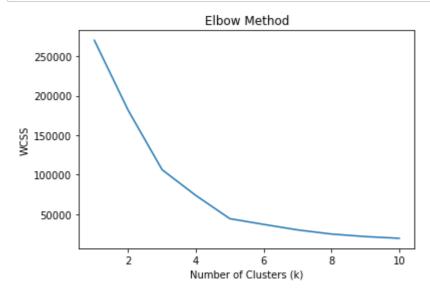
X= data.iloc[:, [3,4]].values

wcss = []

max_clusters = 10

for k in range(1, max_clusters+1):
    kmeans = KMeans(n_clusters=k)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)

plt.plot(range(1, max_clusters+1), wcss)
plt.xlabel('Number of Clusters (k)')
plt.ylabel('WCSS')
plt.title('Elbow Method')
plt.show()
```



In [8]:

```
from sklearn.cluster import KMeans
import numpy as np

X= data.iloc[:, [3,4]].values

optimal_clusters = 3

kmeans = KMeans(n_clusters=optimal_clusters)

kmeans.fit(X)

labels = kmeans.labels_
centers = kmeans.cluster_centers_

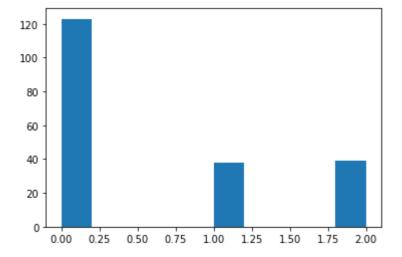
print("Cluster Labels:")
print(labels)

print("Cluster Centers:")
print("Cluster Centers:")
```

Cluster Labels:

In [9]:

```
import matplotlib.pyplot as plt
plt.hist(labels)
plt.show()
```

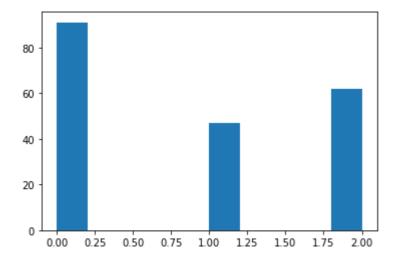


```
In [13]:
```

```
#8. Which attributes are strongly correlated with Spending Score?
import pandas as pd
correlation matrix = data.corr()
spending_score_corr = correlation_matrix['Spending Score (1-100)']
spending_score_corr = spending_score_corr.sort_values(ascending=False)
print(spending_score_corr)
Spending Score (1-100)
                                                                 1.000000
CustomerID
                                                                 0.013835
Annual Income (k$)
                                                                 0.009903
                                                               -0.327227
Age
Name: Spending Score (1-100), dtype: float64
In [14]:
#9. Apply K-means clustering using sklearn with optimal number of clusters along with hig
from sklearn.cluster import KMeans
import pandas as pd
import numpy as np
optimal_clusters = 3
correlation_matrix = data.corr()
highly_correlated_features = correlation_matrix['Spending Score (1-100)'].abs().nlargest(
X = data[highly_correlated_features].values
kmeans = KMeans(n_clusters=optimal_clusters)
kmeans.fit(X)
labels = kmeans.labels
centers = kmeans.cluster_centers_
print("Cluster Labels:")
print(labels)
print("Cluster Centers:")
print(centers)
Cluster Labels:
1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 2 \; 1 \; 
  2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 ]
Cluster Centers:
[[47.78021978 43.05494505]
  [14.59574468 42.95744681]
   [80.74193548 29.56451613]]
```

In [15]:

```
#10. Draw the inferences you find out from the clustering process
import matplotlib.pyplot as plt
plt.hist(labels)
plt.show()
```



In []: