# SRM VALLIAMMAI
# ENGINEERING COLLEGE

(An Autonomous Institution)
SRM Nagar, Kattankulathur-603203.

## DEPARTMENT OF COMPUTER APPLICATIONS

# MC4363- Machine Learning Laboratory

## THIRD SEMSTER MCA

## R-2024

# LAB MANUAL

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# Syllabus

**MC4311 MACHINE LEARNING LABORATORY**

| L | T | P | C |
|---|---|---|---|
| 0 | 0 | 4 | 2 |

**COURSE OBJECTIVES:**

- To understand about data cleaning and data preprocessing
- To familiarize with the Supervised Learning algorithms and implement them in practical situations.
- To familiarize with unsupervised Learning algorithms and carry on the implementation part.
- To involve the students to practice ML algorithms and techniques.
- Learn to use algorithms for real time data sets.

**LIST OF EXPERIMENTS :**

1. Demonstrate how do you structure data in Machine Learning
2. Implement data preprocessing techniques on real time dataset
3. Implement Feature subset selection techniques
4. Demonstrate how will you measure the performance of a machine learning model
5. Write a program to implement the naïve Bayesian classifier for a sample training data set. Compute the accuracy of the classifier, considering few test data sets.
6. Write a program to construct a Bayesian network considering medical data. Use this model to demonstrate the diagnosis of heart patients using the standard Heart Disease Data Set.
7. Apply EM algorithm to cluster a set of data stored in a .CSV file.
8. Write a program to implement k-Nearest Neighbor algorithm to classify the data set.
9. Apply the technique of pruning for a noisy data monk2 data, and derive the decision tree from this data. Analyze the results by comparing the structure of pruned and unpruned tree.
10. Build an Artificial Neural Network by implementing the Backpropagation algorithm and test the same using appropriate data sets
11. Implement Support Vector Classification for linear kernels.
12. Implement Logistic Regression to classify problems such as spam detection. Diabetes predictions and so on.

**TOTAL: 60 PERIODS**

**LAB REQUIREMENTS**:

Python or any ML tools like R



**COURSE OUTCOMES:**

**On completion of the laboratory course, the student should be able to**

**CO1:** apply data preprocessing technique and explore the structure of data to prepare for predictive modeling

**CO2:** understand how to select and train a model and measure the performance.

**CO3:** apply feature selection techniques in Machine Learning

**CO4:** construct Bayesian Network for appropriate problem

**CO5:** learn about parametric and non-parametric machine Learning algorithms and implement to practical situations

## INTERNAL ASSESSMENT FOR LABORATORY

| S.No | Description | Mark |
|---|---|---|
| 1. | Execution | 30 |
| 2. | Record | 10 |
| 3 | Model Exam | 20 |
| | Total | 60 |

# INDEX

| Exercise No. : 01<br>Date: | **Demonstrate how you structure data in Machine Learning** |
|---|---|

## Aim:

Write a program to demonstrate how you structure data in Machine Learning

## Procedure:

Step 1: Start the Jupiter notebook.
Step 2: Create a new Python 3 (ipykernel) file
Step 3:import the library pandas
Step 4: Read the CSV file
Step 5: Print the Dataset
Step 6: End the program

## Program:

In [1]:
```
import pandas as pd
```

In [2]:
```
df=pd.read_csv("student.csv")
```

In [3]:
```
df
```

Out[3]:

| | Reg. no. | M1 | M2 | M3 | result |
|---|---|---|---|---|---|
| **0** | 100 | 654.0 | 984.0 | 45.0 | 0 |
| **1** | 101 | 654.0 | NaN | 2.0 | 1 |
| **2** | 102 | NaN | 65.0 | 45.0 | 0 |
| **3** | 103 | 84.0 | 87.0 | 67.0 | 1 |
| **4** | 104 | 1.0 | 5.0 | 78.0 | 1 |
| **5** | 105 | 67.0 | 34.0 | NaN | 0 |

In [6]:
```
df.head(2)
```

Out[6]:

| | Reg. no. | M1 | M2 | M3 | result |
|---|---|---|---|---|---|
| **0** | 100 | 654.0 | 984.0 | 45.0 | 0 |
| **1** | 101 | 654.0 | NaN | 2.0 | 1 |

In [7]:
```
df.tail(2)
```

Out[7]:

| | Reg. no. | M1 | M2 | M3 | result |
|---|---|---|---|---|---|
| **4** | 104 | 1.0 | 5.0 | 78.0 | 1 |
| **5** | 105 | 67.0 | 34.0 | NaN | 0 |

## Result:

The above program was executed successfully. Hence, the output is verified

| Exercise No. : 02<br>Date: | **Implementing Data Preprocessing techniques on real time dataset** |
|---|---|

## Aim:

Write a program to implementing Data Pre-processing techniques on real time dataset

## Procedure:

Step 1: Start the Jupiter notebook.
Step 2: Create a new Python 3 (ipykernel) file
Step 3: import the library pandas
Step 4: Read the CSV file
Step 5: Cleaning the missing values with NaN
Step 6: Filling the missing values by giving number
Step 7: And Filling the values using forward, backward fill and average value
Step 8: Print the Dataset
Step 9: End the program

## Program:

```
In [1]: import pandas as pd
```

```
In [2]: df=pd.read_csv("student.csv")
```

```
In [3]: df
```

Out[3]:

| | Reg. no. | M1 | M2 | M3 | result |
|---|---|---|---|---|---|
| 0 | 100 | 654.0 | 984.0 | 45.0 | 0 |
| 1 | 101 | 654.0 | NaN | 2.0 | 1 |
| 2 | 102 | NaN | 65.0 | 45.0 | 0 |
| 3 | 103 | 84.0 | 87.0 | 67.0 | 1 |
| 4 | 104 | 1.0 | 5.0 | 78.0 | 1 |
| 5 | 105 | 67.0 | 34.0 | NaN | 0 |

```
In [6]: df.describe()
```

Out[6]:

| | Reg. no. | M1 | M2 | M3 | result |
|---|---|---|---|---|---|
| count | 6.000000 | 5.000000 | 5.00000 | 5.00000 | 6.000000 |
| mean | 102.500000 | 292.000000 | 235.00000 | 47.40000 | 0.500000 |
| std | 1.870829 | 331.910379 | 419.85295 | 29.12559 | 0.547723 |
| min | 100.000000 | 1.000000 | 5.00000 | 2.00000 | 0.000000 |
| 25% | 101.250000 | 67.000000 | 34.00000 | 45.00000 | 0.000000 |
| 50% | 102.500000 | 84.000000 | 65.00000 | 45.00000 | 0.500000 |
| 75% | 103.750000 | 654.000000 | 87.00000 | 67.00000 | 1.000000 |
| max | 105.000000 | 654.000000 | 984.00000 | 78.00000 | 1.000000 |

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6 entries, 0 to 5
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Reg. no.  6 non-null      int64
 1   M1        5 non-null      float64
 2   M2        5 non-null      float64
 3   M3        5 non-null      float64
 4   result    6 non-null      int64
dtypes: float64(3), int64(2)
memory usage: 368.0 bytes
```

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
Reg. no.    0
M1          1
M2          1
M3          1
result      0
dtype: int64
```

In [9]:
```
df.dtypes
```

Out[9]:
```
Reg. no.      int64
M1          float64
M2          float64
M3          float64
result        int64
dtype: object
```

In [10]:
```
df.shape
```

Out[10]:
```
(6, 5)
```

In [11]:
```
df1=df.fillna("n")
```

In [12]:
```
df1
```

Out[12]:

| | Reg. no. | M1 | M2 | M3 | result |
|---|---|---|---|---|---|
| **0** | 100 | 654.0 | 984.0 | 45.0 | 0 |
| **1** | 101 | 654.0 | n | 2.0 | 1 |
| **2** | 102 | n | 65.0 | 45.0 | 0 |
| **3** | 103 | 84.0 | 87.0 | 67.0 | 1 |
| **4** | 104 | 1.0 | 5.0 | 78.0 | 1 |
| **5** | 105 | 67.0 | 34.0 | n | 0 |

In [13]:
```
df2=df.fillna(5)
```

In [14]:
```
df2
```

Out[14]:

| | Reg. no. | M1 | M2 | M3 | result |
|---|---|---|---|---|---|
| 0 | 100 | 654.0 | 984.0 | 45.0 | 0 |
| 1 | 101 | 654.0 | 5.0 | 2.0 | 1 |
| 2 | 102 | 5.0 | 65.0 | 45.0 | 0 |
| 3 | 103 | 84.0 | 87.0 | 67.0 | 1 |
| 4 | 104 | 1.0 | 5.0 | 78.0 | 1 |
| 5 | 105 | 67.0 | 34.0 | 5.0 | 0 |

# dictionary

In [15]:
```
df1=df.fillna({'chol':1,'fbs':2})
```

In [16]:
```
df1.isnull().sum()
df1
```

Out[16]:

| | Reg. no. | M1 | M2 | M3 | result |
|---|---|---|---|---|---|
| 0 | 100 | 654.0 | 984.0 | 45.0 | 0 |
| 1 | 101 | 654.0 | NaN | 2.0 | 1 |
| 2 | 102 | NaN | 65.0 | 45.0 | 0 |
| 3 | 103 | 84.0 | 87.0 | 67.0 | 1 |
| 4 | 104 | 1.0 | 5.0 | 78.0 | 1 |
| 5 | 105 | 67.0 | 34.0 | NaN | 0 |

# Carry forward

In [17]:
```
df1=df.fillna(method="ffill")
df1
```

Out[17]:

| | Reg. no. | M1 | M2 | M3 | result |
|---|---|---|---|---|---|
| 0 | 100 | 654.0 | 984.0 | 45.0 | 0 |
| 1 | 101 | 654.0 | 984.0 | 2.0 | 1 |
| 2 | 102 | 654.0 | 65.0 | 45.0 | 0 |
| 3 | 103 | 84.0 | 87.0 | 67.0 | 1 |
| 4 | 104 | 1.0 | 5.0 | 78.0 | 1 |
| 5 | 105 | 67.0 | 34.0 | 78.0 | 0 |

# Backward fill

In [18]:
```
df1=df.fillna(method="bfill")
df1
```

Out[18]:

| | Reg. no. | M1 | M2 | M3 | result |
|---|---|---|---|---|---|
| **0** | 100 | 654.0 | 984.0 | 45.0 | 0 |
| **1** | 101 | 654.0 | 65.0 | 2.0 | 1 |
| **2** | 102 | 84.0 | 65.0 | 45.0 | 0 |
| **3** | 103 | 84.0 | 87.0 | 67.0 | 1 |
| **4** | 104 | 1.0 | 5.0 | 78.0 | 1 |
| **5** | 105 | 67.0 | 34.0 | NaN | 0 |

# Fill avg value ¶

In [19]:
```
df1=df.interpolate()
df1
```

Out[19]:

| | Reg. no. | M1 | M2 | M3 | result |
|---|---|---|---|---|---|
| **0** | 100 | 654.0 | 984.0 | 45.0 | 0 |
| **1** | 101 | 654.0 | 524.5 | 2.0 | 1 |
| **2** | 102 | 369.0 | 65.0 | 45.0 | 0 |
| **3** | 103 | 84.0 | 87.0 | 67.0 | 1 |
| **4** | 104 | 1.0 | 5.0 | 78.0 | 1 |
| **5** | 105 | 67.0 | 34.0 | 78.0 | 0 |

# Drop NA row/column

In [20]:
```
df1=df.dropna()
df1
```

Out[20]:

| | Reg. no. | M1 | M2 | M3 | result |
|---|---|---|---|---|---|
| **0** | 100 | 654.0 | 984.0 | 45.0 | 0 |
| **3** | 103 | 84.0 | 87.0 | 67.0 | 1 |
| **4** | 104 | 1.0 | 5.0 | 78.0 | 1 |

**Result:**

The above program was executed successfully. Hence, the output is verified

| Exercise No. : 03<br>Date: | **Implementing Feature subset selection techniques** |
|---|---|

## Aim:

Write a program to implement Feature subset selection techniques

## Procedure:

Step 1:Import pandas to create DataFrame
Step 2:Make DataFrame of the given data
Step 3:Variance Threshold feature selector that removes all low-variance features.
Step 4:It will zero variance features
Step 5: Drop the error data
Step 6: Print the DataFrame

## Program:

```
In [1]: import pandas as pd

In [2]: data = pd.DataFrame({"A":[1,2,3,4,5,6],
                             "B":[7,8,9,10,11,12],
                             "C":[0,0,0,0,0,0],
                             "D":[21,54,32,85,35,2]})

In [13]: data
Out[13]:
```

| | A | B | C | D |
|---|---|---|---|---|
| 0 | 1 | 7 | 0 | 21 |
| 1 | 2 | 8 | 0 | 54 |
| 2 | 3 | 9 | 0 | 32 |
| 3 | 4 | 10 | 0 | 85 |
| 4 | 5 | 11 | 0 | 35 |
| 5 | 6 | 12 | 0 | 2 |

```
In [4]: from sklearn.feature_selection import VarianceThreshold

In [5]: var_thres = VarianceThreshold(threshold = 0)

In [6]: var_thres.fit(data)
Out[6]: VarianceThreshold(threshold=0)

In [7]: var_thres.get_support()
Out[7]: array([ True,  True, False,  True])

In [8]: data.columns[var_thres.get_support()]
Out[8]: Index(['A', 'B', 'D'], dtype='object')

In [9]: constant_columns = [column for column in data.columns if column not in data.columns[var_thres.get_support()]]

In [10]: print(len(constant_columns))
1

In [11]: for feature in constant_columns: print(feature)
C
```

In [12]:
```
data.drop(constant_columns, axis = 1)
```
Out[12]:

| | A | B | D |
|---|---|---|---|
| 0 | 1 | 7 | 21 |
| 1 | 2 | 8 | 54 |
| 2 | 3 | 9 | 32 |
| 3 | 4 | 10 | 85 |
| 4 | 5 | 11 | 35 |
| 5 | 6 | 12 | 2 |

# Result:

The above program was executed successfully. Hence, the output is verified

| Exercise No. : 04<br>Date: | **Demonstrate how you will measure the performance of a machine learning model** |
|---|---|

## Aim:

Write a program to demonstrate how you will measure the performance of a machine learning model

## Procedure:

Step 1:Import the Dependencies
Step 2:Load the csv data to a Pandas DataFrame
Step 3:Split the Features and Target
Step 4:Split the Data into Training data & Test Data
Step 5: Train the LogisticRegression model with Training data
Step 6: Find accuracy on training data&accuracy on test data
Step 7: Import the confusion matrix and again find the accuracy of the data
Step 8: Train and Test the data with Precision
Step 9: Recall for training and testing data predictions
Step 10: F1 score for training and testing data predictions

## Program:

In [1]:
```
import pandas as pd
df=pd.read_csv("diabetes.csv")
df
```

Out[1]:

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigreeFunction | Age | Outcome |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 6 | 148 | 72 | 35 | 0 | 33.6 | 0.627 | 50 | 1 |
| **1** | 1 | 85 | 66 | 29 | 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 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **763** | 10 | 101 | 76 | 48 | 180 | 32.9 | 0.171 | 63 | 0 |
| **764** | 2 | 122 | 70 | 27 | 0 | 36.8 | 0.340 | 27 | 0 |
| **765** | 5 | 121 | 72 | 23 | 112 | 26.2 | 0.245 | 30 | 0 |
| **766** | 1 | 126 | 60 | 0 | 0 | 30.1 | 0.349 | 47 | 1 |
| **767** | 1 | 93 | 70 | 31 | 0 | 30.4 | 0.315 | 23 | 0 |

768 rows × 9 columns

In [2]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

In [4]:
```
df['Outcome'].value_counts()
```

Out[4]:
```
0    500
1    268
Name: Outcome, dtype: int64
```

In [5]:
```
X = df.drop(columns='Outcome', axis=1)
Y = df['Outcome']
```

```
In [6]: print(X)

     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0              6      148             72             35        0  33.6
1              1       85             66             29        0  26.6
2              8      183             64              0        0  23.3
3              1       89             66             23       94  28.1
4              0      137             40             35      168  43.1
..           ...      ...            ...            ...      ...   ...
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4

     DiabetesPedigreeFunction  Age
0                       0.627   50
1                       0.351   31
2                       0.672   32
3                       0.167   21
4                       2.288   33
..                        ...  ...
763                     0.171   63
764                     0.340   27
765                     0.245   30
766                     0.349   47
767                     0.315   23

[768 rows x 8 columns]
```

```
In [7]: print(Y)

0      1
1      0
2      1
3      0
4      1
      ..
763    0
764    0
765    0
766    1
767    0
Name: Outcome, Length: 768, dtype: int64
```

```
In [8]: X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,
        stratify=Y, random_state=2)
```

```
In [9]: print(X.shape, X_train.shape, X_test.shape)

(768, 8) (614, 8) (154, 8)
```

```
In [10]: model = LogisticRegression(max_iter=1000)
```

```
In [11]: model.fit(X_train, Y_train)

Out[11]: LogisticRegression(max_iter=1000)
```

```
In [12]: from sklearn.metrics import accuracy_score
```

```
In [13]: X_train_prediction = model.predict(X_train)
         training_data_accuracy = accuracy_score(Y_train, X_train_prediction)
         print(training_data_accuracy)

0.7882736156351792
```

```
In [14]: print('Accuracy on Training data :', round(training_data_accuracy*100, 2),
         '%')

Accuracy on Training data : 78.83 %
```

```
In [15]: X_test_prediction = model.predict(X_test)
         test_data_accuracy = accuracy_score(Y_test, X_test_prediction)
         print(test_data_accuracy)

0.7597402597402597
```

```
In [16]: print('Accuracy on Training data :', round(test_data_accuracy*100, 2),
         '%')

Accuracy on Training data : 75.97 %
```

In [15]:
```
X_test_prediction = model.predict(X_test)
test_data_accuracy = accuracy_score(Y_test, X_test_prediction)
print(test_data_accuracy)
```

```
0.7597402597402597
```

In [16]:
```
print('Accuracy on Training data :', round(test_data_accuracy*100, 2),
'%')
```

```
Accuracy on Training data : 75.97 %
```

In [20]:
```
import seaborn as sns
sns.heatmap(cf_matrix, annot=True)
```

Out[20]:
```
<AxesSubplot:>
```

In [21]:
```
from sklearn.metrics import precision_score
precision_train = precision_score(Y_train, X_train_prediction)
print('Training data Precision =', precision_train)
```

```
Training data Precision = 0.7530120481927711
```

In [22]:
```
precision_test = precision_score(Y_test, X_test_prediction)
print('Test data Precision =', precision_test)
```

```
Test data Precision = 0.717948717948718
```

In [23]:
```
from sklearn.metrics import recall_score
recall_train = recall_score(Y_train, X_train_prediction)
print('Training data Recall =', recall_train)
```

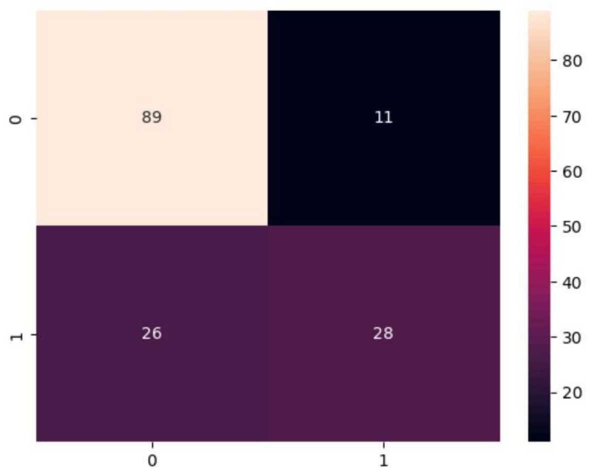
```
Training data Recall = 0.5841121495327103
```

In [24]:
```
recall_test = recall_score(Y_test, X_test_prediction)
print('Test data Recall =', recall_test)
```

```
Test data Recall = 0.5185185185185185
```

In [25]:
```
from sklearn.metrics import f1_score
f1_score_train = f1_score(Y_train, X_train_prediction)
print('Training data F1 Score =', f1_score_train)
```

```
Training data F1 Score = 0.6578947368421052
```



In [26]:
```
f1_score_test = recall_score(Y_test, X_test_prediction)
print('Test data F1 Score =', f1_score_test)
```

```
Test data F1 Score = 0.5185185185185185
```

In [27]:
```
def precision_recall_f1_score(true_labels, pred_labels):
    precision_value = precision_score(true_labels, pred_labels)
    recall_value = recall_score(true_labels, pred_labels)
    f1_score_value = f1_score(true_labels, pred_labels)
    print('Precision =',precision_value)
    print('Recall =',recall_value)
    print('F1 Score =',f1_score_value)
```

In [28]:
```
precision_recall_f1_score(Y_train, X_train_prediction)
```

```
Precision = 0.7530120481927711
Recall = 0.5841121495327103
F1 Score = 0.6578947368421052
```

In [29]:
```
precision_recall_f1_score(Y_test, X_test_prediction)
```

```
Precision = 0.717948717948718
Recall = 0.5185185185185185
F1 Score = 0.6021505376344085
```

## Result:

The above program executed successfully. Hence output verified

| Exercise No. : 05A<br>Date: | **Write a program to implement the naïve Bayesian classification for a sample training data set** |
|---|---|

## Aim:

Write a program to implement the naïve Bayesian classification for a sample training data set. Compute the accuracy of the classifier, with Titanic test data sets.

## Procedure:

Step 1:Import the Dependencies
Step 2:Load the csv data to a Pandas DataFrame
Step 3:Split the Features and Target
Step 4:Split the Data into Training data & Test Data
Step 5: Train the GaussianNB model with Training data
Step 6: Find accuracy on training data&accuracy on test data
Step 7: Use the cross validation and again find the accuracy of the data with training data.

## Program:

```
In [1]: import pandas as pd
```

```
In [24]: df = pd.read_csv("titanic.csv")
         df.head()
```

Out[24]:

| | PassengerId | Name | Pclass | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked | Survived |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | Braund, Mr. Owen Harris | 3 | male | 22.0 | 1 | 0 | A/5 21171 | 7.2500 | NaN | S | 0 |
| 1 | 2 | Cumings, Mrs. John Bradley (Florence Briggs Th... | 1 | female | 38.0 | 1 | 0 | PC 17599 | 71.2833 | C85 | C | 1 |
| 2 | 3 | Heikkinen, Miss. Laina | 3 | female | 26.0 | 0 | 0 | STON/O2. 3101282 | 7.9250 | NaN | S | 1 |
| 3 | 4 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | 1 | female | 35.0 | 1 | 0 | 113803 | 53.1000 | C123 | S | 1 |
| 4 | 5 | Allen, Mr. William Henry | 3 | male | 35.0 | 0 | 0 | 373450 | 8.0500 | NaN | S | 0 |

```
In [25]: df.drop(['PassengerId','Name','SibSp','Parch','Ticket','Cabin','Embarked'],axis='columns',inplace=True)
         df.head()
```

Out[25]:

| | Pclass | Sex | Age | Fare | Survived |
|---|---|---|---|---|---|
| 0 | 3 | male | 22.0 | 7.2500 | 0 |
| 1 | 1 | female | 38.0 | 71.2833 | 1 |
| 2 | 3 | female | 26.0 | 7.9250 | 1 |
| 3 | 1 | female | 35.0 | 53.1000 | 1 |
| 4 | 3 | male | 35.0 | 8.0500 | 0 |

```
In [26]: inputs = df.drop('Survived',axis='columns')
         target = df.Survived
```

```
In [5]: # inputs.Sex = inputs.Sex.map({'male': 1, 'female': 2})
```

```
In [27]: dummies = pd.get_dummies(inputs.Sex)
         dummies.head(3)
```

Out[27]:

| | female | male |
|---|---|---|
| 0 | 0 | 1 |
| 1 | 1 | 0 |
| 2 | 1 | 0 |

```
In [28]: inputs = pd.concat([inputs,dummies],axis='columns')
         inputs.head(3)
```

Out[28]:

| | Pclass | Sex | Age | Fare | female | male |
|---|---|---|---|---|---|---|
| 0 | 3 | male | 22.0 | 7.2500 | 0 | 1 |
| 1 | 1 | female | 38.0 | 71.2833 | 1 | 0 |
| 2 | 3 | female | 26.0 | 7.9250 | 1 | 0 |

In [29]:
```
inputs.drop(['Sex','male'],axis='columns',inplace=True)
inputs.head(3)
```

Out[29]:

| | Pclass | Age | Fare | female |
|---|---|---|---|---|
| 0 | 3 | 22.0 | 7.2500 | 0 |
| 1 | 1 | 38.0 | 71.2833 | 1 |
| 2 | 3 | 26.0 | 7.9250 | 1 |

In [30]:
```
inputs.columns[inputs.isna().any()]
```

Out[30]:
```
Index(['Age'], dtype='object')
```

In [10]:
```
inputs.Age[:10]
```

Out[10]:
```
0    22.0
1    38.0
2    26.0
3    35.0
4    35.0
5     NaN
6    54.0
7     2.0
8    27.0
9    14.0
Name: Age, dtype: float64
```

In [31]:
```
inputs.Age = inputs.Age.fillna(inputs.Age.mean())
inputs.head()
```

Out[31]:

| | Pclass | Age | Fare | female |
|---|---|---|---|---|
| 0 | 3 | 22.0 | 7.2500 | 0 |
| 1 | 1 | 38.0 | 71.2833 | 1 |
| 2 | 3 | 26.0 | 7.9250 | 1 |
| 3 | 1 | 35.0 | 53.1000 | 1 |
| 4 | 3 | 35.0 | 8.0500 | 0 |

In [12]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(inputs,target,test_size=0.3)
```

In [13]:
```
from sklearn.naive_bayes import GaussianNB
model = GaussianNB()
```

In [14]:
```
model.fit(X_train,y_train)
```

Out[14]:
```
GaussianNB(priors=None, var_smoothing=1e-09)
```

In [15]:
```
model.score(X_test,y_test)
```

Out[15]:
```
0.7835820895522388
```

In [16]:
```
X_test[0:10]
```

Out[16]:

| | Pclass | Age | Fare | female | male |
|---|---|---|---|---|---|
| 309 | 1 | 30.000000 | 56.9292 | 1 | 0 |
| 839 | 1 | 29.699118 | 29.7000 | 0 | 1 |
| 110 | 1 | 47.000000 | 52.0000 | 0 | 1 |
| 872 | 1 | 33.000000 | 5.0000 | 0 | 1 |
| 235 | 3 | 29.699118 | 7.5500 | 1 | 0 |
| 411 | 3 | 29.699118 | 6.8583 | 0 | 1 |
| 32 | 3 | 29.699118 | 7.7500 | 1 | 0 |
| 562 | 2 | 28.000000 | 13.5000 | 0 | 1 |
| 542 | 3 | 11.000000 | 31.2750 | 1 | 0 |
| 250 | 3 | 29.699118 | 7.2500 | 0 | 1 |

In [17]:
```
y_test[0:10]
```

```
Out[17]: 309    1
         839    1
         110    0
         872    0
         235    0
         411    0
         32     1
         562    0
         542    0
         250    0
         Name: Survived, dtype: int64
```

```
In [18]: model.predict(X_test[0:10])
```

```
Out[18]: array([1, 0, 0, 0, 1, 0, 1, 0, 1, 0], dtype=int64)
```

```
In [19]: model.predict_proba(X_test[:10])
```

```
Out[19]: array([[0.00455992, 0.99544008],
                [0.91382024, 0.08617976],
                [0.88164575, 0.11835425],
                [0.92347978, 0.07652022],
                [0.09084386, 0.90915614],
                [0.99093305, 0.00906695],
                [0.09094857, 0.90905143],
                [0.97923786, 0.02076214],
                [0.0516967 , 0.9483033 ],
                [0.9909573 , 0.0090427 ]])
```

```
In [34]: from sklearn.model_selection import cross_val_score
         cross_val_score(GaussianNB(),X_train, y_train, cv=5)
```

```
Out[34]: array([0.75396825, 0.784     , 0.76612903, 0.82258065, 0.77419355])
```

**Result:**

The above program executed successfully. Hence output verified

| Exercise No. : 05B<br>Date: | **Write a program to implement the naïve Bayesian classification for a sample training data set** |
|---|---|

## Aim:

Write a program to implement the naïve Bayesian classification for a sample training data set. Compute the accuracy of the classifier, with Spam test data sets.

## Procedure:

Step 1:Import the Dependencies
Step 2:Load the csv data to a Pandas DataFrame
Step 3: Categorize the target of data
Step 4:Splitting the Data into Training data & Test Data
Step 5: Import CountVectorizer to vectorize the data
Step 6: Import the MultinomialNB model and find the accuracy of the data
Step 7: Import the Pipeline model and find the accuracy of the data by cross validating the vectorized data with trained data.

## Program:

In [1]:
```
import pandas as pd
df = pd.read_csv("spam.csv")
df.head()
```

Out[1]:

| | Category | Message |
|---|---|---|
| 0 | ham | Go until jurong point, crazy.. Available only ... |
| 1 | ham | Ok lar... Joking wif u oni... |
| 2 | spam | Free entry in 2 a wkly comp to win FA Cup fina... |
| 3 | ham | U dun say so early hor... U c already then say... |
| 4 | ham | Nah I don't think he goes to usf, he lives aro... |

In [2]:
```
df.groupby('Category').describe()
```

Out[2]:

| | Message | | | |
|---|---|---|---|---|
| | count | unique | top | freq |
| Category | | | | |
| ham | 4825 | 4516 | Sorry, I'll call later | 30 |
| spam | 747 | 641 | Please call our customer service representativ... | 4 |

In [3]:
```
df['spam']=df['Category'].apply(lambda x: 1 if x=='spam' else 0)
df.head()
```

Out[3]:

| | Category | Message | spam |
|---|---|---|---|
| 0 | ham | Go until jurong point, crazy.. Available only ... | 0 |
| 1 | ham | Ok lar... Joking wif u oni... | 0 |
| 2 | spam | Free entry in 2 a wkly comp to win FA Cup fina... | 1 |
| 3 | ham | U dun say so early hor... U c already then say... | 0 |
| 4 | ham | Nah I don't think he goes to usf, he lives aro... | 0 |

In [4]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df.Message,df.spam)
```

```
In [5]: from sklearn.feature_extraction.text import CountVectorizer
        v = CountVectorizer()
        X_train_count = v.fit_transform(X_train.values)
        X_train_count.toarray()[:2]

Out[5]: array([[0, 0, 0, ..., 0, 0, 0],
               [0, 0, 0, ..., 0, 0, 0]], dtype=int64)

In [6]: from sklearn.naive_bayes import MultinomialNB
        model = MultinomialNB()
        model.fit(X_train_count,y_train)

Out[6]: MultinomialNB()

In [8]: X_test_count = v.transform(X_test)
        model.score(X_test_count, y_test)

Out[8]: 0.9877961234745154

In [9]: from sklearn.pipeline import Pipeline
        clf = Pipeline([
            ('vectorizer', CountVectorizer()),
            ('nb', MultinomialNB())
        ])

In [10]: clf.fit(X_train, y_train)

Out[10]: Pipeline(steps=[('vectorizer', CountVectorizer()), ('nb', MultinomialNB())])

In [11]: clf.score(X_test,y_test)

Out[11]: 0.9877961234745154

In [12]: clf.predict(emails)

Out[12]: array([0, 1], dtype=int64)
```

## Result:

The above program executed successfully. Hence output verified

| Exercise No. : 06<br>Date: | **UsingBayesian model to demonstrate the diagnosis a heart patients using the standard heart disease data set.** |
|---|---|

## Aim:

Write a program to construct a Bayesian network considering medical data. Use this model to demonstrate the diagnosis a heart patients using the standard heart disease data set.

## Procedure:

Step 1:Import the dependencies
Step 2:Load the csv data to a Pandas Data Frame
Step 3:Import BayesianModel and train the data
Step 4:Import MaximumLikelihoodEstimator and estimate the maximum likelihood of the data
Step 5:Use the ValidationElimination method on the model to inferencing the data.
Step 6:Display the maximum likelihood probability of the target data.

## Program:

```
In [1]: import numpy as np
        import pandas as pd
        import csv
```

```
In [2]: from pgmpy.estimators import MaximumLikelihoodEstimator
        from pgmpy.models import BayesianModel
        from pgmpy.inference import VariableElimination
```

```
In [3]: hD = pd.read_csv('heart.csv')
        hD = hD.replace('?', np.nan)
        hD
```

Out[3]:

| | age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | oldpeak | slope | ca | thal | target |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 63 | 1 | 3.0 | 145.0 | 233.0 | 1.0 | 0.0 | 150.0 | 0.0 | 2.3 | 0.0 | 0.0 | 1 | 1 |
| **1** | 37 | 1 | 2.0 | 130.0 | 250.0 | 0.0 | 1.0 | 187.0 | 0.0 | 3.5 | 0.0 | 0.0 | 2 | 1 |
| **2** | 41 | 0 | 1.0 | 130.0 | 204.0 | 0.0 | 0.0 | 172.0 | 0.0 | 1.4 | 2.0 | 0.0 | 2 | 1 |
| **3** | 56 | 1 | 1.0 | 120.0 | 236.0 | 0.0 | 1.0 | 178.0 | 0.0 | 0.8 | 2.0 | 0.0 | 2 | 1 |
| **4** | 57 | 0 | 0.0 | 120.0 | NaN | 0.0 | 1.0 | 163.0 | 1.0 | 0.6 | 2.0 | 0.0 | 2 | 1 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **298** | 57 | 0 | 0.0 | 140.0 | 241.0 | 0.0 | 1.0 | 123.0 | 1.0 | 0.2 | 1.0 | 0.0 | 3 | 0 |
| **299** | 45 | 1 | 3.0 | 110.0 | 264.0 | 0.0 | 1.0 | 132.0 | 0.0 | 1.2 | 1.0 | 0.0 | 3 | 0 |
| **300** | 68 | 1 | 0.0 | 144.0 | 193.0 | 1.0 | 1.0 | 141.0 | 0.0 | 3.4 | 1.0 | 2.0 | 3 | 0 |
| **301** | 57 | 1 | 0.0 | 130.0 | 131.0 | 0.0 | 1.0 | 115.0 | 1.0 | 1.2 | 1.0 | 1.0 | 3 | 0 |
| **302** | 57 | 0 | 1.0 | 130.0 | 236.0 | 0.0 | 0.0 | 174.0 | 0.0 | 0.0 | 1.0 | 1.0 | 2 | 0 |

303 rows × 14 columns

```
In [9]: model = BayesianModel([('age','target'),('sex','target'),('trestbps','target'),('cp','target'),('target','restecg'),
        ('target','chol'),('target','fbs'),('target','thalach'),('target','exang'),('target','oldpeak'),('target','slope'),
        ('target','ca'),('target','thal')])
```

```
In [5]: print('\n Learning CPD using Maximum Likelihood estimators')
        model.fit(hD,estimator = MaximumLikelihoodEstimator)
```

```
 Learning CPD using Maximum Likelihood estimators
```

```
In [6]: print('\nInferencing with Bayesian Network')
        hD_infer = VariableElimination(model)
```

```
Inferencing with Bayesian Network
```

```
In [10]: print('\n 1. Probability of heatdesease given evidence = restecg :1')
         q1 = hD_infer.query(variables = ['target'], evidence = {'restecg':1})
         print(q1)
```

```
 1. Probability of heatdesease given evidence = restecg :1
+-----------+---------------+
| target    |   phi(target) |
+===========+===============+
| target(0) |        0.4031 |
+-----------+---------------+
| target(1) |        0.5969 |
+-----------+---------------+
```

In [8]:
```
print('\n 2. Probability of heatdesease given evidence = cp:2')
q2 = hD_infer.query(variables = ['target'], evidence = {'cp':2})
print(q2)
```

```
 2. Probability of heatdesease given evidence = cp:2
+-----------+---------------+
| target    |   phi(target) |
+===========+===============+
| target(0) |        0.4862 |
+-----------+---------------+
| target(1) |        0.5138 |
+-----------+---------------+
```

## Result:

The above program executed successfully. Hence output verified

| Exercise No. : 07<br>Date: | **Apply EM algorithm to cluster a set of data stored in a .csv file** |
|---|---|

## Aim:

Write a program to apply EM algorithm to cluster a set of data stored in a .csv file

## Procedure:

Step 1:Imported libraries and dataset
Step 2:loading data-set for EM algorithm
Step 3:Defining EM Model
Step 4:Training of the model
Step 5:Predicting classes for our data
Step 6:Accuracy of EM Model

## Program:

In [1]:
```
#Imported libraries and dataset

from sklearn import datasets

from sklearn.cluster import KMeans

from sklearn.utils import shuffle

import numpy as np

import pandas as pd
```

In [2]:
```
#loading data-set for EM algorithm

iris = datasets.load_iris()

X = pd.DataFrame(iris.data)

Y = pd.DataFrame(iris.target)
```

In [3]:
```
#Defining EM Model
from sklearn.mixture import GaussianMixture
model2=GaussianMixture(n_components=3,random_state=3425)

#Training of the model

model2.fit(X)
```

Out[3]:
```
GaussianMixture(n_components=3, random_state=3425)
```

In [4]:
```
#Predicting classes for our data

uu= model2.predict(X)

#Accuracy of EM Model

from sklearn.metrics import confusion_matrix

cm=confusion_matrix(Y,uu)

print(cm)

from sklearn.metrics import accuracy_score

print(accuracy_score(Y,uu))
```

```
[[ 0  0 50]
 [45  5  0]
 [ 0 50  0]]
0.03333333333333333
```

## Result:

The above program executed successfully. Hence output verified

| Exercise No. : 08<br>Date: | **Implement k-Nearest Neighbour algorithm to classify the dataset** |
|---|---|

## Aim:

Write a program to implement k-Nearest Neighbour algorithm toclassify the dataset

## Procedure:

Step 1:
Step 2:
Step 3:
Step 4:
Step 5:
Step 6:

## Program:

```
In [1]: import pandas as pd
        from sklearn.datasets import load_iris
        iris=load_iris()
```

```
In [3]: iris.feature_names
```

```
Out[3]: ['sepal length (cm)',
         'sepal width (cm)',
         'petal length (cm)',
         'petal width (cm)']
```

```
In [4]: iris.target_names
```

```
Out[4]: array(['setosa', 'versicolor', 'virginica'], dtype='<U10')
```

```
In [5]: df=pd.DataFrame(iris.data,columns=iris.feature_names)
```

```
In [6]: df.head()
```

Out[6]:

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) |
|---|---|---|---|---|
| 0 | 5.1 | 3.5 | 1.4 | 0.2 |
| 1 | 4.9 | 3.0 | 1.4 | 0.2 |
| 2 | 4.7 | 3.2 | 1.3 | 0.2 |
| 3 | 4.6 | 3.1 | 1.5 | 0.2 |
| 4 | 5.0 | 3.6 | 1.4 | 0.2 |

```
In [7]: df['target']=iris.target
        df.head()
```

Out[7]:

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | target |
|---|---|---|---|---|---|
| 0 | 5.1 | 3.5 | 1.4 | 0.2 | 0 |
| 1 | 4.9 | 3.0 | 1.4 | 0.2 | 0 |
| 2 | 4.7 | 3.2 | 1.3 | 0.2 | 0 |
| 3 | 4.6 | 3.1 | 1.5 | 0.2 | 0 |
| 4 | 5.0 | 3.6 | 1.4 | 0.2 | 0 |

In [8]:
```
df[df.target==1].head()
```

Out[8]:

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | target |
|---|---|---|---|---|---|
| **50** | 7.0 | 3.2 | 4.7 | 1.4 | 1 |
| **51** | 6.4 | 3.2 | 4.5 | 1.5 | 1 |
| **52** | 6.9 | 3.1 | 4.9 | 1.5 | 1 |
| **53** | 5.5 | 2.3 | 4.0 | 1.3 | 1 |
| **54** | 6.5 | 2.8 | 4.6 | 1.5 | 1 |

In [9]:
```
df[df.target==2].head()
```

Out[9]:

| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | target |
|---|---|---|---|---|---|
| **100** | 6.3 | 3.3 | 6.0 | 2.5 | 2 |
| **101** | 5.8 | 2.7 | 5.1 | 1.9 | 2 |
| **102** | 7.1 | 3.0 | 5.9 | 2.1 | 2 |
| **103** | 6.3 | 2.9 | 5.6 | 1.8 | 2 |
| **104** | 6.5 | 3.0 | 5.8 | 2.2 | 2 |

In [18]:
```
df['flower_name']=df.target.apply(lambda x:iris.target_names[x])
```

In [19]:
```
df.head()
```

Out[19]:

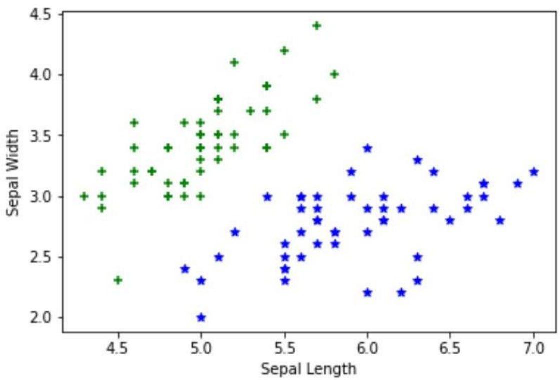
| | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) | target | flower_name |
|---|---|---|---|---|---|---|
| **0** | 5.1 | 3.5 | 1.4 | 0.2 | 0 | setosa |
| **1** | 4.9 | 3.0 | 1.4 | 0.2 | 0 | setosa |
| **2** | 4.7 | 3.2 | 1.3 | 0.2 | 0 | setosa |
| **3** | 4.6 | 3.1 | 1.5 | 0.2 | 0 | setosa |
| **4** | 5.0 | 3.6 | 1.4 | 0.2 | 0 | setosa |

In [20]:
```
df0=df[:50]
df1=df[50:100]
df2=df[100:]
```

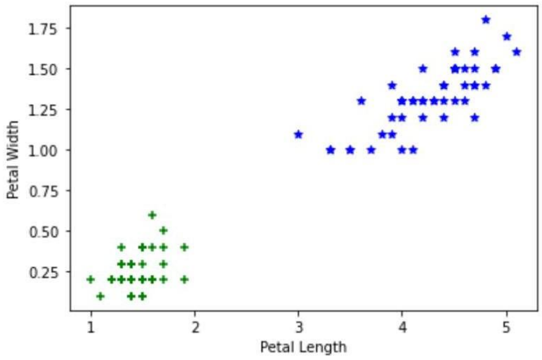
In [21]:
```
import matplotlib.pyplot as plt
%matplotlib inline
```

In [31]:
```
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.scatter(df0['sepal length (cm)'],df0['sepal width (cm)'],color="green",marker='+')
plt.scatter(df1['sepal length (cm)'],df1['sepal width (cm)'],color="blue",marker='*')
```

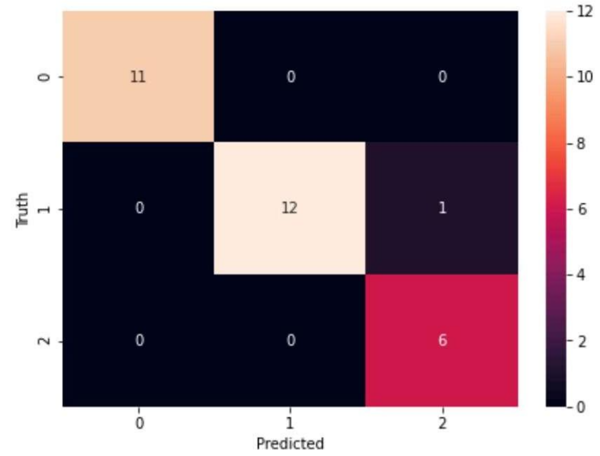
Out[31]:
```
<matplotlib.collections.PathCollection at 0x2388bc49cd0>
```



```
In [32]: plt.xlabel('Petal Length')
         plt.ylabel('Petal Width')
         plt.scatter(df0['petal length (cm)'],df0['petal width (cm)'],color="green",marker='+')
         plt.scatter(df1['petal length (cm)'],df1['petal width (cm)'],color="blue",marker='*')

Out[32]: <matplotlib.collections.PathCollection at 0x2388c9cf1f0>
```




```
In [23]: from sklearn.model_selection import train_test_split
         x=df.drop(['target','flower_name'],axis='columns')
         y=df.target
         x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=1)

In [24]: len(x_train)

Out[24]: 120

In [26]: len(x_test)

Out[26]: 30

In [34]: from sklearn.neighbors import KNeighborsClassifier
         knn=KNeighborsClassifier(n_neighbors=10)

In [35]: knn.fit(x_train,y_train)

Out[35]: KNeighborsClassifier(n_neighbors=10)

In [36]: knn.score(x_test,y_test)

Out[36]: 0.9666666666666667

In [37]: knn.predict([[4.8,3.0,1.5,0.3]])

Out[37]: array([0])

In [38]: from sklearn.metrics import confusion_matrix
         y_pred=knn.predict(x_test)
         cm=confusion_matrix(y_test,y_pred)

In [39]: cm

Out[39]: array([[11,  0,  0],
                [ 0, 12,  1],
                [ 0,  0,  6]], dtype=int64)

In [40]: %matplotlib inline
         import matplotlib.pyplot as plt
         import seaborn as sn
         plt.figure(figsize=(7,5))
         sn.heatmap(cm,annot=True)
         plt.xlabel('Predicted')
         plt.ylabel('Truth')

Out[40]: Text(42.0, 0.5, 'Truth')
```




```
In [41]: from sklearn.metrics import classification_report

In [42]: print(classification_report(y_test,y_pred))
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        11
           1       1.00      0.92      0.96        13
           2       0.86      1.00      0.92         6

    accuracy                           0.97        30
   macro avg       0.95      0.97      0.96        30
weighted avg       0.97      0.97      0.97        30
```

## Result:

The above program executed successfully. Hence output verified

| Exercise No. : 09<br>Date: | **Derive a decision tree from the dataset** |
|---|---|

## Aim:

Write a program to drive a decision tree from the dataset

## Procedure:

Step 1:
Step 2:
Step 3:
Step 4:
Step 5:
Step 6:

## Program:

```
In [1]: import pandas as pd
```

```
In [2]: df = pd.read_csv("salaries.csv")
        df.head()
```

Out[2]:

| | company | job | degree | salary_more_then_100k |
|---|---|---|---|---|
| 0 | google | sales executive | bachelors | 0 |
| 1 | google | sales executive | masters | 0 |
| 2 | google | business manager | bachelors | 1 |
| 3 | google | business manager | masters | 1 |
| 4 | google | computer programmer | bachelors | 0 |

```
In [3]: inputs = df.drop('salary_more_then_100k',axis='columns')
```

```
In [4]: target = df['salary_more_then_100k']
```

```
In [5]: from sklearn.preprocessing import LabelEncoder
        le_company = LabelEncoder()
        le_job = LabelEncoder()
        le_degree = LabelEncoder()
```

```
In [6]: inputs['company_n'] = le_company.fit_transform(inputs['company'])
        inputs['job_n'] = le_job.fit_transform(inputs['job'])
        inputs['degree_n'] = le_degree.fit_transform(inputs['degree'])
```

```
In [7]: inputs
```

Out[7]:

| | company | job | degree | company_n | job_n | degree_n |
|---|---|---|---|---|---|---|
| 0 | google | sales executive | bachelors | 2 | 2 | 0 |
| 1 | google | sales executive | masters | 2 | 2 | 1 |
| 2 | google | business manager | bachelors | 2 | 0 | 0 |
| 3 | google | business manager | masters | 2 | 0 | 1 |
| 4 | google | computer programmer | bachelors | 2 | 1 | 0 |
| 5 | google | computer programmer | masters | 2 | 1 | 1 |
| 6 | abc pharma | sales executive | masters | 0 | 2 | 1 |
| 7 | abc pharma | computer programmer | bachelors | 0 | 1 | 0 |
| 8 | abc pharma | business manager | bachelors | 0 | 0 | 0 |
| 9 | abc pharma | business manager | masters | 0 | 0 | 1 |
| 10 | facebook | sales executive | bachelors | 1 | 2 | 0 |
| 11 | facebook | sales executive | masters | 1 | 2 | 1 |
| 12 | facebook | business manager | bachelors | 1 | 0 | 0 |

In [8]:
```
inputs_n = inputs.drop(['company','job','degree'],axis='columns')
```

In [9]:
```
inputs_n
```

Out[9]:

| | company_n | job_n | degree_n |
|---|---|---|---|
| 0 | 2 | 2 | 0 |
| 1 | 2 | 2 | 1 |
| 2 | 2 | 0 | 0 |
| 3 | 2 | 0 | 1 |
| 4 | 2 | 1 | 0 |
| 5 | 2 | 1 | 1 |
| 6 | 0 | 2 | 1 |
| 7 | 0 | 1 | 0 |
| 8 | 0 | 0 | 0 |
| 9 | 0 | 0 | 1 |
| 10 | 1 | 2 | 0 |
| 11 | 1 | 2 | 1 |
| 12 | 1 | 0 | 0 |
| 13 | 1 | 0 | 1 |
| 14 | 1 | 1 | 0 |

In [10]:
```
target
```

Out[10]:
```
0     0
1     0
2     1
3     1
4     0
5     1
6     0
7     0
8     0
9     1
10    1
11    1
12    1
13    1
14    1
15    1
Name: salary_more_then_100k, dtype: int64
```

In [11]:
```
from sklearn import tree
model = tree.DecisionTreeClassifier()
```

In [12]:
```
model.fit(inputs_n, target)
```

Out[12]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

In [13]:
```
model.score(inputs_n,target)
```

Out[13]:
```
1.0
```

**Is salary of Google, Computer Engineer, Bachelors degree > 100 k ?**

In [14]:
```
model.predict([[2,1,0]])
```

Out[14]:
```
array([0], dtype=int64)
```

**Is salary of Google, Computer Engineer, Masters degree > 100 k ?**

In [15]:
```
model.predict([[2,1,1]])
```

Out[15]:
```
array([1], dtype=int64)
```

## Result:

The above program executed successfully. Hence output verified

| Exercise No. : 10<br>Date: | **Implementing the back propagation algorithm and test the same using appropriate dataset** |
|---|---|

## Aim:

Write a program to build an Artificial Neural Network by implementing the back propagation algorithm and test the same using appropriate dataset

## Procedure:

Step 1:
Step 2:
Step 3:
Step 4:
Step 5:
Step 6:

## Program:

```
In [1]: import numpy as np
X = np.array(([2, 9], [1, 5], [3, 6]), dtype=float)
y = np.array(([92], [86], [89]), dtype=float) # scale units
X = X/np.amax(X, axis=0) #maximum of X array
y = y/100 # maximum test score is 100

class NeuralNetwork(object):
    def __init__ (self): #parameters
        self.inputSize = 2
        self.outputSize = 1
        self.hiddenSize = 3
        self.W1 = np.random.randn(self.inputSize, self.hiddenSize)
        self.W2 = np.random.randn(self.hiddenSize, self.outputSize)

    def feedForward(self, X):
        self.z = np.dot(X, self.W1)
        self.z2 = self.sigmoid(self.z)
        self.z3 = np.dot(self.z2, self.W2)
        output = self.sigmoid(self.z3)
        return output

    def sigmoid(self, s, deriv=False):
        if (deriv == True):
            return s * (1 - s)
        return 1/(1 + np.exp(-s))

    def backward(self, X, y, output): #backward propogate through the network
        self.output_error = y - output # error in output
        self.output_delta = self.output_error * self.sigmoid(output, deriv=True)
        self.z2_error = self.output_delta.dot(self.W2.T) #z2 error: how much our hidden layer weights
        self.z2_delta = self.z2_error * self.sigmoid(self.z2, deriv=True) #applying derivative of sig
        self.W1 += X.T.dot(self.z2_delta) # adjusting first set (input -> hidden) weights
        self.W2 += self.z2.T.dot(self.output_delta) # adjusting second set (hidden -> output) weights
    def train(self, X, y):
        output = self.feedForward(X)
        self.backward(X, y, output)

NN = NeuralNetwork()
for i in range(1000): #trains the NN 1000 times
    if (i % 100 == 0):
        print("Loss: " + str(np.mean(np.square(y - NN.feedForward(X)))))
        NN.train(X, y)
print("Input: " + str(X))
print("Actual Output: " + str(y))
print("Loss: " + str(np.mean(np.square(y - NN.feedForward(X)))))
print("\n")
print("Predicted Output: " + str(NN.feedForward(X)))
```

```
Loss: 0.024912562840868836
Loss: 0.020568438885881255
Loss: 0.017167958121637485
Loss: 0.014471137378264548
Loss: 0.012306361746843379
Loss: 0.010549272872305953
Loss: 0.009108544221234353
Loss: 0.007916223149021984
Loss: 0.006921107548652352
Loss: 0.006084151847431011
Input: [[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual Output: [[0.92]
 [0.86]
 [0.89]]
Loss: 0.005375242340215718


Predicted Output: [[0.85079209]
 [0.80977176]
 [0.7961218 ]]
```

## Result:

The above program executed successfully. Hence output verified

| Exercise No. : 11<br>Date: | **Implement Support Vector Classification for linear kernels** |
|---|---|

## Aim:

Write a program to implement Support Vector Classification for linear kernels

## Procedure:

Step 1:Import necessary dataset from sklearn datasets
Step 2:Import the dependencies
Step 3:Separate the target from the features
Step 4:Split the data into training and test data
Step 5:Import the Standard Scaler and implement it on training and test data
Step 6:Import the SVM model and implement it on the scaled data by setting the kernel as linear
Step 7: Display the accuracy on both training and test data

## Program:

In [1]:
```
from sklearn.datasets import load_breast_cancer
```

In [2]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.svm import SVC
import pandas as pd
```

In [3]:
```
a = load_breast_cancer()
a.target_names
```

Out[3]:
```
array(['malignant', 'benign'], dtype='<U9')
```

In [4]:
```
df=pd.DataFrame(a.data, columns = list(a.feature_names))
df['diagnosis'] = a.target
df.head(4)
```

Out[4]:

| | mean radius | mean texture | mean perimeter | mean area | mean smoothness | mean compactness | mean concavity | mean concave points | mean symmetry | mean fractal dimension | ... | worst texture | worst perimeter | worst area | worst smoothness | compa |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 17.99 | 10.38 | 122.80 | 1001.0 | 0.11840 | 0.27760 | 0.3001 | 0.14710 | 0.2419 | 0.07871 | ... | 17.33 | 184.60 | 2019.0 | 0.1622 | |
| 1 | 20.57 | 17.77 | 132.90 | 1326.0 | 0.08474 | 0.07864 | 0.0869 | 0.07017 | 0.1812 | 0.05667 | ... | 23.41 | 158.80 | 1956.0 | 0.1238 | |
| 2 | 19.69 | 21.25 | 130.00 | 1203.0 | 0.10960 | 0.15990 | 0.1974 | 0.12790 | 0.2069 | 0.05999 | ... | 25.53 | 152.50 | 1709.0 | 0.1444 | |
| 3 | 11.42 | 20.38 | 77.58 | 386.1 | 0.14250 | 0.28390 | 0.2414 | 0.10520 | 0.2597 | 0.09744 | ... | 26.50 | 98.87 | 567.7 | 0.2098 | |

In [5]:
```
X_train, X_test, y_train, y_test = train_test_split(a.data, a.target,stratify=a.target, random_state=42)
print(f"X_train shape: {X_train.shape}")
print(f"X_test shape: {X_test.shape}")
print(f"y_train shape: {y_train.shape}")
print(f"y_test shape: {y_test.shape}")
```

```
X_train shape: (426, 30)
X_test shape: (143, 30)
y_train shape: (426,)
y_test shape: (143,)
```

In [6]:
```
svm = SVC(kernel='linear')
svm.fit(X_train, y_train)
```

Out[6]:
```
SVC(kernel='linear')
```

In [7]:
```
print(f'Accuracy on training subset is: {svm.score(X_train, y_train):.3f}')
print(f'Accuracy on test subset is: {svm.score(X_test, y_test):.3f}')
```

```
Accuracy on training subset is: 0.962
Accuracy on test subset is: 0.951
```

In [8]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
In [9]: svm = SVC(kernel='linear')
        svm.fit(X_train_scaled, y_train)

Out[9]: SVC(kernel='linear')

In [10]: print(f'Accuracy on training subset is: {svm.score(X_train_scaled, y_train):3f}')
         print(f'Accuracy on test subset is: {svm.score(X_test_scaled, y_test):.3f}')

         Accuracy on training subset is: 0.990610
         Accuracy on test subset is: 0.986
```

## Result:

The above program executed successfully. Hence output verified

| Exercise No. : 12A<br>Date: | **Implement Logistic Regression to classify problems such as Spam detection** |
|---|---|

## Aim:

Write a program to implement Logistic Regression to classify problems such as Spam detection

## Procedure:

Step 1:Import the Dependencies
Step 2:Load the csv data to a Pandas DataFrame
Step 3:Split the Features and Target
Step 4:Split the Data into Training data & Test Data
Step 5: Train the LogisticRegression model with Training data
Step 6: Find accuracy on training data&accuracy on test data

## Program:

```
In [ ]: import pandas as pd
        import numpy as np
        from sklearn.model_selection import train_test_split
        from sklearn.linear_model import LogisticRegression
```

```
In [ ]: data = pd.read_csv('spam.csv')
```

```
In [22]: data.head()
```

Out[22]:

| | Category | Message |
|---|---|---|
| 0 | ham | Go until jurong point, crazy.. Available only ... |
| 1 | ham | Ok lar... Joking wif u oni... |
| 2 | spam | Free entry in 2 a wkly comp to win FA Cup fina... |
| 3 | ham | U dun say so early hor... U c already then say... |
| 4 | ham | Nah I don't think he goes to usf, he lives aro... |

```
In [23]: data['Message'].value_counts()
```

```
Out[23]: Sorry, I'll call later
         30
         I cant pick the phone right now. Pls send a message
         12
         Ok...
         10
         Ok.
4
Say this slowly.? GOD,I LOVE YOU &amp; I NEED YOU,CLEAN MY HEART WITH YOUR BLOOD.Send this to Ten special people &amp; u c mira
cle tomorrow, do it,pls,pls do it...     4

..
Haha, my friend tyler literally just asked if you could get him a dubsack
1
Try neva mate!!
1
Ur cash-balance is currently 500 pounds - to maximize ur cash-in now send GO to 86688 only 150p/msg. CC: 08718720201 PO BOX 11
4/14 TCR/W1                             1
Its just the effect of irritation. Just ignore it
1
Booked ticket for pongal?
1
Name: Message, Length: 5157, dtype: int64
```

```
In [39]: from sklearn import preprocessing
         c1=preprocessing.LabelEncoder()
         data['Category']=c1.fit_transform(data['Category'])
         data['Message']=c1.fit_transform(data['Message'])
```

```
In [40]: x = data.drop(columns='Message',axis=1)
```

```
In [41]: y=data['Message']
```

```
In [42]: x
```

```
Out[42]:
```

| | Category |
|---|---|
| 0 | 0 |
| 1 | 0 |
| 2 | 1 |
| 3 | 0 |
| 4 | 0 |
| ... | ... |
| 5567 | 1 |
| 5568 | 0 |
| 5569 | 0 |
| 5570 | 0 |
| 5571 | 0 |

5572 rows × 1 columns

```
In [43]: y
Out[43]: 0       1080
         1       3126
         2        999
         3       4121
         4       2781
                 ...
         5567    4025
         5568    4596
         5569    3313
         5570    3932
         5571    3437
         Name: Message, Length: 5572, dtype: int32

In [49]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2)

In [50]: print(x.shape,x_train.shape,x_test.shape)

         (5572, 1) (4457, 1) (1115, 1)

In [61]: model=LogisticRegression(max_iter=1000)

In [62]: model.fit(x_train,y_train)
Out[62]: LogisticRegression(max_iter=1000)

In [63]: from sklearn.metrics import accuracy_score

In [64]: x_train_prediction=model.predict(x_train)
         trained_data_accuracy=accuracy_score(y_train,x_train_prediction)
         print(trained_data_accuracy)

         0.006057886470720216

In [65]: print('Accuracy on training data:',round(trained_data_accuracy*100,2),'%')

         Accuracy on training data: 0.61 %

In [67]: x_test_prediction=model.predict(x_test)
         test_data_accuracy=accuracy_score(y_test,x_test_prediction)
         print(test_data_accuracy)

         0.006278026905829596

In [68]: print('Accuracy on test data:',round(test_data_accuracy*100,2),'%')

         Accuracy on test data: 0.63 %
```

## Result:

The above program executed successfully. Hence output verified

| Exercise No. : 12B<br>Date: | **Implement Logistic Regression to classify problems such as Diabetics detection** |
|---|---|

## Aim:

Write a program to implement Logistic Regression to classify problems such as Spam detection

## Procedure:

Step 1:Import the Dependencies
Step 2:Load the CSV data to a Pandas DataFrame
Step 3:Split the Features and Target
Step 4:Split the Data into Training data & Test Data
Step 5: Train the LogisticRegression model with Training data
Step 6: Find accuracy on training data&accuracy on test data

## Program:

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

In [2]:
```
data = pd.read_csv('diabetes.csv')
```

In [3]:
```
data.head()
```

Out[3]:

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigreeFunction | Age | Outcome |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 6 | 148 | 72 | 35 | 0 | 33.6 | 0.627 | 50 | 1 |
| 1 | 1 | 85 | 66 | 29 | 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 |

In [6]:
```
data['Outcome'].value_counts()
```

Out[6]:
```
0    500
1    268
Name: Outcome, dtype: int64
```

In [7]:
```
x=data.drop(columns='Outcome',axis=1)
```

In [9]:
```
y=data['Outcome']
```

In [10]:
```
x
```

Out[10]:

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigreeFunction | Age |
|---|---|---|---|---|---|---|---|---|
| 0 | 6 | 148 | 72 | 35 | 0 | 33.6 | 0.627 | 50 |
| 1 | 1 | 85 | 66 | 29 | 0 | 26.6 | 0.351 | 31 |
| 2 | 8 | 183 | 64 | 0 | 0 | 23.3 | 0.672 | 32 |
| 3 | 1 | 89 | 66 | 23 | 94 | 28.1 | 0.167 | 21 |
| 4 | 0 | 137 | 40 | 35 | 168 | 43.1 | 2.288 | 33 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 763 | 10 | 101 | 76 | 48 | 180 | 32.9 | 0.171 | 63 |
| 764 | 2 | 122 | 70 | 27 | 0 | 36.8 | 0.340 | 27 |
| 765 | 5 | 121 | 72 | 23 | 112 | 26.2 | 0.245 | 30 |
| 766 | 1 | 126 | 60 | 0 | 0 | 30.1 | 0.349 | 47 |
| 767 | 1 | 93 | 70 | 31 | 0 | 30.4 | 0.315 | 23 |

768 rows × 8 columns

In [11]:
```
y
```

```
Out[11]: 0      1
         1      0
         2      1
         3      0
         4      1
               ..
         763    0
         764    0
         765    0
         766    1
         767    0
         Name: Outcome, Length: 768, dtype: int64
```

```
In [12]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,stratify=y,random_state=2)
```

```
In [17]: print(x.shape,x_train.shape,x_test.shape)

         (768, 8) (614, 8) (154, 8)
```

```
In [18]: from sklearn.metrics import accuracy_score
```

```
In [20]: model=LogisticRegression(max_iter=1000)
         model.fit(x_train,y_train)
         x_train_prediction=model.predict(x_train)
         trained_data_accuracy=accuracy_score(y_train,x_train_prediction)
         print(trained_data_accuracy)

         0.7882736156351792
```

```
In [21]: print('Accuracy on training data:',round(trained_data_accuracy*100,2),'%')

         Accuracy on training data: 78.83 %
```

```
In [22]: x_test_prediction=model.predict(x_test)
         test_data_accuracy=accuracy_score(y_test,x_test_prediction)
         print(test_data_accuracy)

         0.7597402597402597
```

```
In [23]: print('Accuracy on test data:',round(test_data_accuracy*100,2),'%')

         Accuracy on test data: 75.97 %
```

## Result:

The above program executed successfully. Hence output verified

**Exercise No. : 13** **Customer Segmentation using K-Means Clustering**

**Date:**

## Aim:

Write a program Customer Segmentation using K-Means Clustering

## Procedure:

Step 1:Loading the data from csv file to a Pandas DataFrame
Step 2:First 5 rows in the dataframe
Step 3:Finding the number of rows and columns
Step 4:Getting some informations about the dataset
Step 5:Checking for missing values
Step 6:Finding wcss value for different number of clusters
Step 7: Plot an elbow graph
Step 8:Optimum Number of Clusters = 5
Step 9: Training the k-Means Clustering Model
Step 10: Return a label for each data point based on their cluster
Step 11: Visualizing all the Clusters

## Program:

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
```

In [2]:
```
# loading the data from csv file to a Pandas DataFrame
customer_data = pd.read_csv('Mall_Customers.csv')
```

In [3]:
```
# first 5 rows in the dataframe
customer_data.head()
```

Out[3]:

| | 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 |

In [4]:
```
# finding the number of rows and columns
customer_data.shape
```

Out[4]: (200, 5)

In [5]:
```
# getting some informations about the dataset
customer_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   CustomerID              200 non-null    int64
 1   Gender                  200 non-null    object
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

In [6]:
```
# checking for missing values
customer_data.isnull().sum()
```

Out[6]:
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

.

In [7]:
```
X = customer_data.iloc[:,[3,4]].values
```

In [8]:
```
print(X)
```

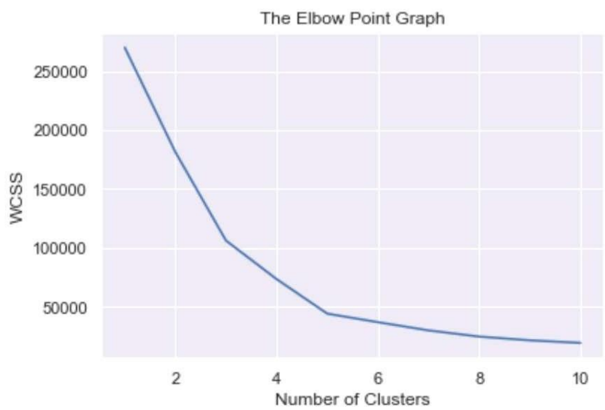
```
[[ 15  39]
 [ 15  81]
 [ 16   6]
 [ 16  77]
 [ 17  40]
 [ 17  76]
 [ 18   6]
 [ 18  94]
 [ 19   3]
 [ 19  72]
 [ 19  14]
 [ 19  99]
 [ 20  15]
 [ 20  77]
 [ 20  13]
 [ 20  79]
 [ 21  35]
 [ 21  66]
 [ 23  29]
```

## Choosing the number of clusters

WCSS -> Within Clusters Sum of Squares

In [9]:
```
# finding wcss value for different number of clusters

wcss = []

for i in range(1,11):
  kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
  kmeans.fit(X)

  wcss.append(kmeans.inertia_)
```

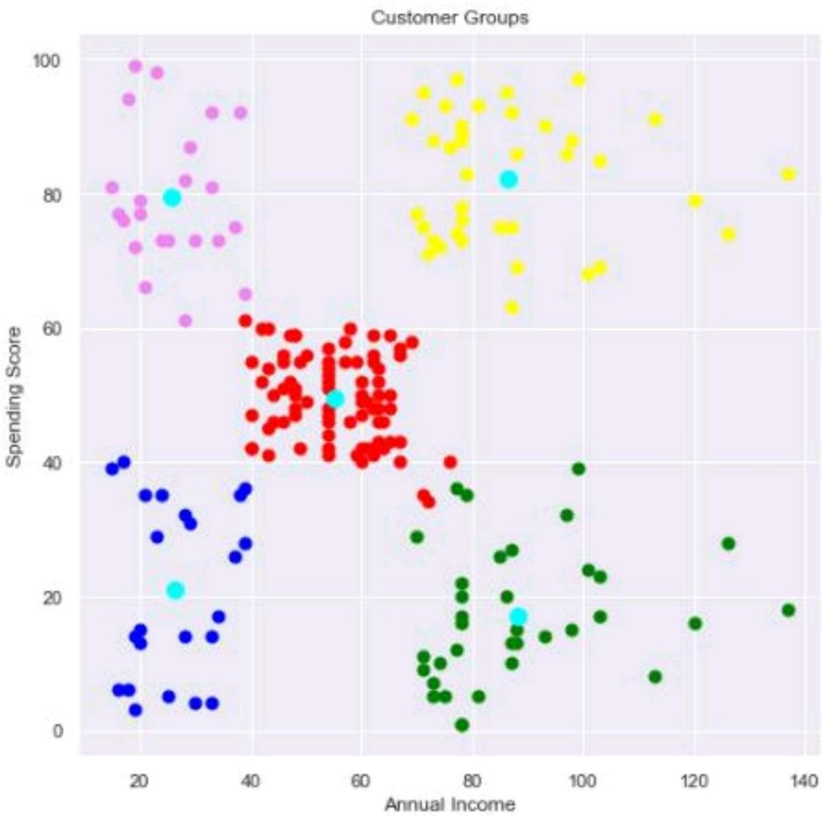
In [10]:
```
# plot an elbow graph

sns.set()
plt.plot(range(1,11), wcss)
plt.title('The Elbow Point Graph')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
```



In [11]:
```python
#Optimum Number of Clusters = 5

#Training the k-Means Clustering Model

kmeans = KMeans(n_clusters=5, init='k-means++', random_state=0)

# return a label for each data point based on their cluster
Y = kmeans.fit_predict(X)

print(Y)
```

```
[4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4
 3 4 3 4 3 4 1 4 3 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 2 0 2 1 2 0 2 0 2 1 2 0 2 0 2 0 2 0 2 1 2 0 2 0 2
 0 2 0 2 0 2 0 2 0 2 0 2 0 2 0 2 0 2 0 2 0 2 0 2 0 2 0 2 0 2 0 2 0 2 0 2 0
 2 0 2 0 2 0 2 0 2 0 2 0 2 0 2]
```

In [12]:
```python
# 5 Clusters - 0, 1, 2, 3, 4
# Visualizing all the Clusters
# plotting all the clusters and their Centroids

plt.figure(figsize=(8,8))
plt.scatter(X[Y==0,0], X[Y==0,1], s=50, c='green', label='Cluster 1')
plt.scatter(X[Y==1,0], X[Y==1,1], s=50, c='red', label='Cluster 2')
plt.scatter(X[Y==2,0], X[Y==2,1], s=50, c='yellow', label='Cluster 3')
plt.scatter(X[Y==3,0], X[Y==3,1], s=50, c='violet', label='Cluster 4')
plt.scatter(X[Y==4,0], X[Y==4,1], s=50, c='blue', label='Cluster 5')
# plot the centroids
plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:,1], s=100, c='cyan', label='Centroids')

plt.title('Customer Groups')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.show()
```




**Result:**

The above program executed successfully. Hence output verified

# Lab Viva Voce Questions

| No. | Question | Answer |
|---|---|---|
| 1 | What is overfitting? | Model performs well on training data but poorly on unseen data. |
| 2 | What is underfitting? | Model is too simple, can't capture the data pattern. |
| 3 | Define accuracy. | Ratio of correctly predicted observations to total. |
| 4 | What is precision? | TP / (TP + FP) |
| 5 | What is recall? | TP / (TP + FN) |
| 6 | What is F1 Score? | Harmonic mean of precision and recall. |
| 7 | What is confusion matrix? | Table for evaluating classifier performance. |
| 8 | Define entropy in decision trees. | Measure of impurity in a dataset. |
| 9 | What is Gini index? | Another impurity measure used in trees. |
| 10 | Difference between supervised and unsupervised learning? | Labeled vs. unlabeled data. |
| 11 | What is a hyperparameter? | Parameters set before training (e.g., learning rate). |
| 12 | What is cross-validation? | Splitting data for better evaluation. |
| 13 | What is Naïve Bayes based on? | Bayes Theorem with independence assumption. |
| 14 | What is a kernel in SVM? | Function to transform input space. |
| 15 | When to use logistic regression? | For binary classification problems. |
| 16 | Why use feature scaling? | Ensures features contribute equally. |
| 17 | What is PCA? | Technique for dimensionality reduction. |
| 18 | What is a ROC curve? | Plot of TPR vs. FPR. |
| 19 | What is AUC? | Area under ROC curve. |
| 20 | What is EM algorithm? | Iterative optimization for clustering. |
| 21 | Define KNN. | Classifies based on nearest neighbors. |
| 22 | What is distance metric in KNN? | Usually Euclidean. |
| 23 | What is a Bayesian Network? | Graphical model for probabilistic relationships. |
| 24 | What is missing value imputation? | Replacing missing data using strategy. |

| No. | Question | Answer |
|---|---|---|
| 25 | What is standardization? | Mean = 0, SD = 1. |
| 26 | What is normalization? | Scaling to [0,1] range. |
| 27 | Define epoch. | One pass over the training data. |
| 28 | Define learning rate. | Controls step size in weight update. |
| 29 | What is pruning in decision tree? | Reducing size to avoid overfitting. |
| 30 | What is early stopping? | Stop training when validation error increases. |
| 31 | Why use backpropagation? | To minimize error in neural nets. |
| 32 | What is weight decay? | Regularization technique. |
| 33 | What is stratified sampling? | Maintains class proportions. |
| 34 | Difference between generative and discriminative models? | Generative models learn data distribution. |
| 35 | What is dropout? | Regularization in neural nets. |
| 36 | What is the sigmoid function? | Activation function (0,1). |
| 37 | What is ReLU? | f(x)=max(0,x) |
| 38 | What is softmax? | Converts logits to probabilities. |
| 39 | What is one-hot encoding? | Binary representation of categorical data. |
| 40 | What is label encoding? | Converts categories to integers. |
| 41 | What is class imbalance? | Unequal class distribution. |
| 42 | How to handle class imbalance? | Use SMOTE, class weights, etc. |
| 43 | What is ensemble learning? | Combining multiple models. |
| 44 | What is bagging? | Parallel ensemble (e.g., Random Forest). |
| 45 | What is boosting? | Sequential ensemble (e.g., XGBoost). |
| 46 | What is a decision boundary? | Surface separating classes. |
| 47 | What is curse of dimensionality? | High-dimensional data becomes sparse. |
| 48 | What is bias? | Error due to simplistic assumptions. |
| 49 | What is variance? | Error due to sensitivity to small changes. |
| 50 | What is grid search? | Tuning hyperparameters using exhaustive search. |