Logistic Regression

Import libraries and load dataset

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

import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```python
df = pd.read_csv('Social_Network_Ads.csv')

df.head()
```

Out[2]:

	Age	EstimatedSalary	Purchased
0	19	19000	0
1	35	20000	0
2	26	43000	0
3	27	57000	0
4	19	76000	0

In [3]:
```python
df.isnull().sum()
```

Out[3]:
```
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64
```

observations :

```
* There are no missing values.
```

Separating independent and dependent data

In [4]:
```python
# independent features
x = df.drop(columns = ['Purchased'], axis = 1)

# dependent features
y = df['Purchased']
```

Train Test Split

In [5]:
```python
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3, random_state = 42)
```

Standard Scaling

In [6]:
```python
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
```

Model Training

In [7]:
```python
from sklearn.linear_model import LogisticRegression

classifier = LogisticRegression()
classifier.fit(x_train, y_train)
```

Out[7]:
```
LogisticRegression()
```

Prediction

In [8]:
```python
y_pred = classifier.predict(x_test)

y_pred
```

Out[8]:
```
array([0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0,
       0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1,
       0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0,
       0, 0, 1, 1, 1, 0, 0, 0, 0, 0], dtype=int64)
```

Evaluation

In [9]:
```python
from sklearn.metrics import confusion_matrix, accuracy_score

print(confusion_matrix(y_test, y_pred), '\n')
print(accuracy_score(y_test, y_pred))
```

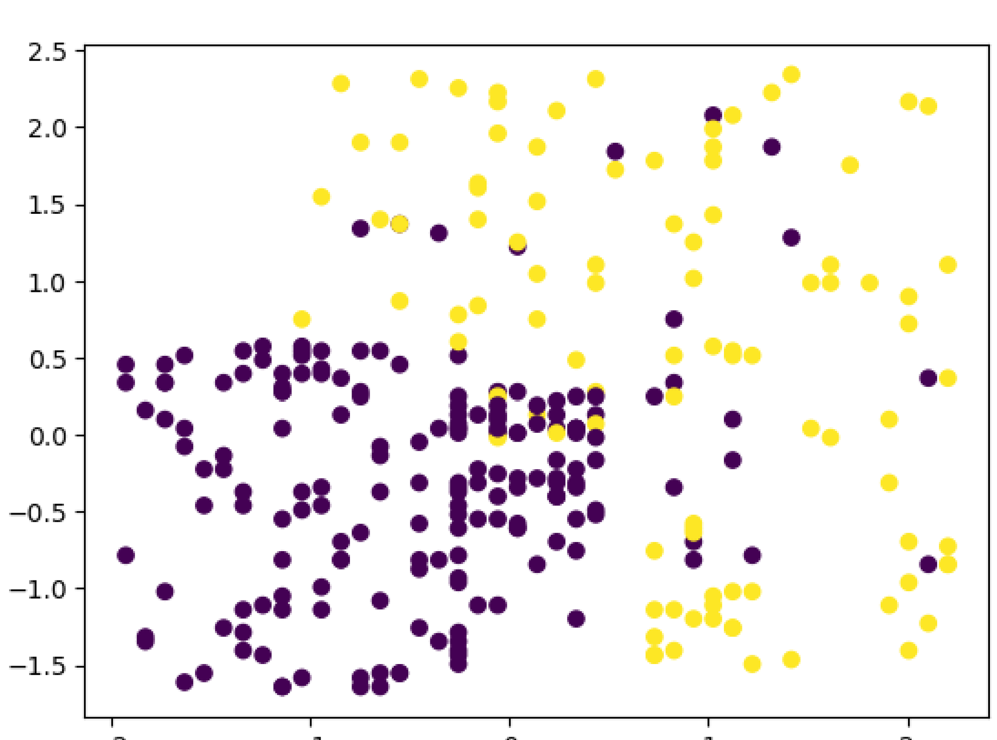
```
[[71  2]
 [16 31]]

0.85
```

1. Visualising training result

In [29]:
```python
plt.scatter(x = x_train[:, 0], y = x_train[:, 1], c = y_train)
```

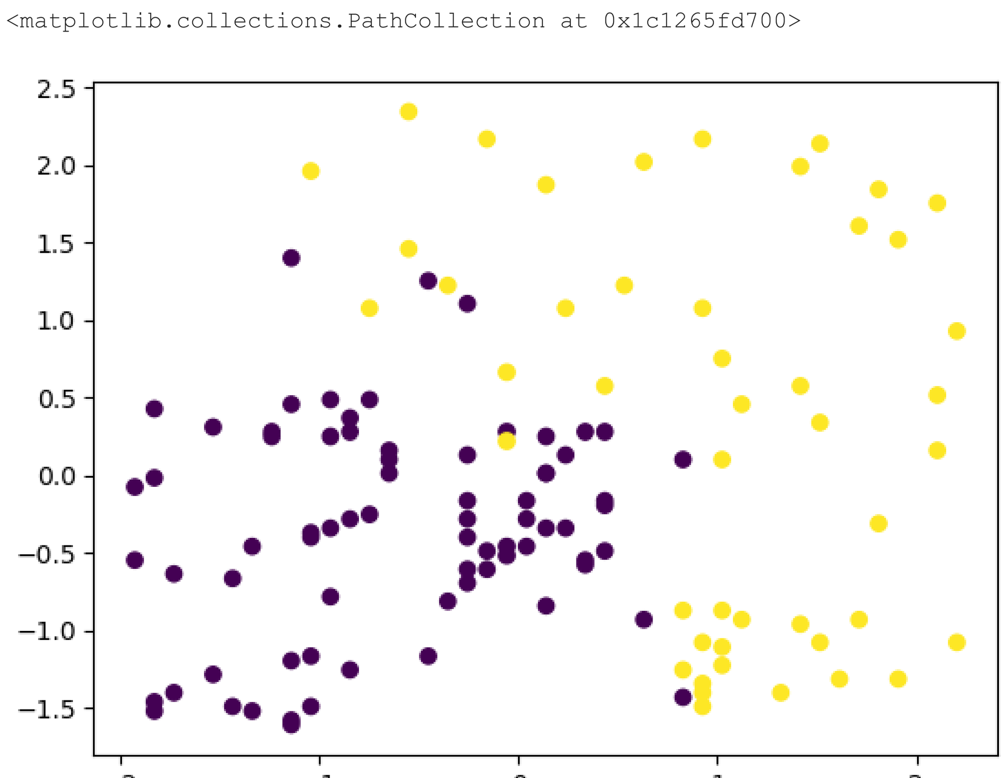
Out[29]:
```
<matplotlib.collections.PathCollection at 0x1c1a9b97820>
```



2. Visualising test result

In [30]:
```python
plt.scatter(x = x_test[:, 0], y = x_test[:, 1], c = y_test)
```

Out[30]:
```
<matplotlib.collections.PathCollection at 0x1c1265fd700>
```



Logistic Regression

Import library, load dataset and understand data

In [1]:
```python
from sklearn.datasets import load_iris
```

In [2]:
```python
dataset = load_iris()
```

In [3]:
```python
dataset
```

Out[3]:
```
{'data': array([[5.1, 3.5, 1.4, 0.2],
        [4.9, 3. , 1.4, 0.2],
        [4.7, 3.2, 1.3, 0.2],
        [4.6, 3.1, 1.5, 0.2],
        [5. , 3.6, 1.4, 0.2],
        [5.4, 3.9, 1.7, 0.4],
        [4.6, 3.4, 1.4, 0.3],
        [5. , 3.4, 1.5, 0.2],
        [4.4, 2.9, 1.4, 0.2],
        [4.9, 3.1, 1.5, 0.1],
        [5.4, 3.7, 1.5, 0.2],
        [4.8, 3.4, 1.6, 0.2],
        [4.8, 3. , 1.4, 0.1],
        [4.3, 3. , 1.1, 0.1],
        [5.8, 4. , 1.2, 0.2],
        [5.7, 4.4, 1.5, 0.4],
        [5.4, 3.9, 1.3, 0.4],
        [5.1, 3.5, 1.4, 0.3],
        [5.7, 3.8, 1.7, 0.3],
        [5.1, 3.8, 1.5, 0.3],
        [5.4, 3.4, 1.7, 0.2],
        [5.1, 3.7, 1.5, 0.4],
        [4.6, 3.6, 1. , 0.2],
        [5.1, 3.3, 1.7, 0.5],
        [4.8, 3.4, 1.9, 0.2],
        [5. , 3. , 1.6, 0.2],
        [5. , 3.4, 1.6, 0.4],
        [5.2, 3.5, 1.5, 0.2],
        [5.2, 3.4, 1.4, 0.2],
        [4.7, 3.2, 1.6, 0.2],
        [4.8, 3.1, 1.6, 0.2],
        [5.4, 3.4, 1.5, 0.4],
        [5.2, 4.1, 1.5, 0.1],
        [5.5, 4.2, 1.4, 0.2],
        [4.9, 3.1, 1.5, 0.2],
        [5. , 3.2, 1.2, 0.2],
        [5.5, 3.5, 1.3, 0.2],
        [4.9, 3.6, 1.4, 0.1],
        [4.4, 3. , 1.3, 0.2],
        [5.1, 3.4, 1.5, 0.2],
        [5. , 3.5, 1.3, 0.3],
        [4.5, 2.3, 1.3, 0.3],
        [4.4, 3.2, 1.3, 0.2],
        [5. , 3.5, 1.6, 0.6],
        [5.1, 3.8, 1.9, 0.4],
        [4.8, 3. , 1.4, 0.3],
        [5.1, 3.8, 1.6, 0.2],
        [4.6, 3.2, 1.4, 0.2],
        [5.3, 3.7, 1.5, 0.2],
        [5. , 3.3, 1.4, 0.2],
        [7. , 3.2, 4.7, 1.4],
        [6.4, 3.2, 4.5, 1.5],
        [6.9, 3.1, 4.9, 1.5],
        [5.5, 2.3, 4. , 1.3],
        [6.5, 2.8, 4.6, 1.5],
        [5.7, 2.8, 4.5, 1.3],
        [6.3, 3.3, 4.7, 1.6],
        [4.9, 2.4, 3.3, 1. ],
        [6.6, 2.9, 4.6, 1.3],
        [5.2, 2.7, 3.9, 1.4],
        [5. , 2. , 3.5, 1. ],
        [5.9, 3. , 4.2, 1.5],
        [6. , 2.2, 4. , 1. ],
        [6.1, 2.9, 4.7, 1.4],
        [5.6, 2.9, 3.6, 1.3],
        [6.7, 3.1, 4.4, 1.4],
        [5.6, 3. , 4.5, 1.5],
        [5.8, 2.7, 4.1, 1. ],
        [6.2, 2.2, 4.5, 1.5],
        [5.6, 2.5, 3.9, 1.1],
        [5.9, 3.2, 4.8, 1.8],
        [6.1, 2.8, 4. , 1.3],
        [6.3, 2.5, 4.9, 1.5],
        [6.1, 2.8, 4.7, 1.2],
        [6.4, 2.9, 4.3, 1.3],
        [6.6, 3. , 4.4, 1.4],
        [6.8, 2.8, 4.8, 1.4],
        [6.7, 3. , 5. , 1.7],
        [6. , 2.9, 4.5, 1.5],
        [5.7, 2.6, 3.5, 1. ],
        [5.5, 2.4, 3.8, 1.1],
        [5.5, 2.4, 3.7, 1. ],
        [5.8, 2.7, 3.9, 1.2],
        [6. , 2.7, 5.1, 1.6],
        [5.4, 3. , 4.5, 1.5],
        [6. , 3.4, 4.5, 1.6],
        [6.7, 3.1, 4.7, 1.5],
        [6.3, 2.3, 4.4, 1.3],
        [5.6, 3. , 4.1, 1.3],
        [5.5, 2.5, 4. , 1.3],
        [5.5, 2.6, 4.4, 1.2],
        [6.1, 3. , 4.6, 1.4],
        [5.8, 2.6, 4. , 1.2],
        [5. , 2.3, 3.3, 1. ],
        [5.6, 2.7, 4.2, 1.3],
        [5.7, 3. , 4.2, 1.2],
        [5.7, 2.9, 4.2, 1.3],
        [6.2, 2.9, 4.3, 1.3],
        [5.1, 2.5, 3. , 1.1],
        [5.7, 2.8, 4.1, 1.3],
        [6.3, 3.3, 6. , 2.5],
        [5.8, 2.7, 5.1, 1.9],
        [7.1, 3. , 5.9, 2.1],
        [6.3, 2.9, 5.6, 1.8],
        [6.5, 3. , 5.8, 2.2],
        [7.6, 3. , 6.6, 2.1],
        [4.9, 2.5, 4.5, 1.7],
        [7.3, 2.9, 6.3, 1.8],
        [6.7, 2.5, 5.8, 1.8],
        [7.2, 3.6, 6.1, 2.5],
        [6.5, 3.2, 5.1, 2. ],
        [6.4, 2.7, 5.3, 1.9],
        [6.8, 3. , 5.5, 2.1],
        [5.7, 2.5, 5. , 2. ],
        [5.8, 2.8, 5.1, 2.4],
        [6.4, 3.2, 5.3, 2.3],
        [6.5, 3. , 5.5, 1.8],
        [7.7, 3.8, 6.7, 2.2],
        [7.7, 2.6, 6.9, 2.3],
        [6. , 2.2, 5. , 1.5],
        [6.9, 3.2, 5.7, 2.3],
        [5.6, 2.8, 4.9, 2. ],
        [7.7, 2.8, 6.7, 2. ],
        [6.3, 2.7, 4.9, 1.8],
        [6.7, 3.3, 5.7, 2.1],
        [7.2, 3.2, 6. , 1.8],
        [6.2, 2.8, 4.8, 1.8],
        [6.1, 3. , 4.9, 1.8],
        [6.4, 2.8, 5.6, 2.1],
        [7.2, 3. , 5.8, 1.6],
        [7.4, 2.8, 6.1, 1.9],
        [7.9, 3.8, 6.4, 2. ],
        [6.4, 2.8, 5.6, 2.2],
        [6.3, 2.8, 5.1, 1.5],
        [6.1, 2.6, 5.6, 1.4],
        [7.7, 3. , 6.1, 2.3],
        [6.3, 3.4, 5.6, 2.4],
        [6.4, 3.1, 5.5, 1.8],
        [6. , 3. , 4.8, 1.8],
        [6.9, 3.1, 5.4, 2.1],
        [6.7, 3.1, 5.6, 2.4],
        [6.9, 3.1, 5.1, 2.3],
        [5.8, 2.7, 5.1, 1.9],
        [6.8, 3.2, 5.9, 2.3],
        [6.7, 3.3, 5.7, 2.5],
        [6.7, 3. , 5.2, 2.3],
        [6.3, 2.5, 5. , 1.9],
        [6.5, 3. , 5.2, 2. ],
        [6.2, 3.4, 5.4, 2.3],
        [5.9, 3. , 5.1, 1.8]]),
 'target': array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 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, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2]),
 'frame': None,
 'target_names': array(['setosa', 'versicolor', 'virginica'], dtype='<U10'),
 'DESCR': '.. _iris_dataset:\n\nIris plants dataset\n--------------------\n\n**Data Set Characteristics:**\n\n    :Number of Instances: 150 (50 in each of three classes)\n    :Number of Attributes: 4 numeric, predictiv
e attributes and the class\n    :Attribute Information:\n        - sepal length in cm\n        - sepal width in cm\n        - petal length in cm\n        - petal width in cm\n        - class:\n                - Iris-Se
tosa\n                - Iris-Versicolour\n                - Iris-Virginica\n                \n    :Summary Statistics:\n\n    ============== ==== ==== ======= ===== ====================\n                    Min  Max
Mean    SD   Class Correlation\n    ============== ==== ==== ======= ===== ====================\n    sepal length:   4.3  7.9   5.84   0.83    0.7826\n    sepal width:    2.0  4.4   3.05   0.43   -0.4194\n    petal len
gth:   1.0  6.9   3.76   1.76    0.9490  (high!)\n    petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)\n    ============== ==== ==== ======= ===== ====================\n\n    :Missing Attribute Values: None\n
:Class Distribution: 33.3% for each of 3 classes.\n    :Creator: R.A. Fisher\n    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)\n    :Date: July, 1988\n\nThe famous Iris database, first used by Sir R.A. Fishe
r. The dataset is taken\nfrom Fisher\'s paper. Note that it\'s the same as in R, but not as in the UCI\nMachine Learning Repository, which has two wrong data points.\n\nThis is perhaps the best known database to be fou
nd in the\npattern recognition literature.  Fisher\'s paper is a classic in the field and\nis referenced frequently to this day.  (See Duda & Hart, for example.)  The\ndata set contains 3 classes of 50 instances each,
where each class refers to a\ntype of iris plant.  One class is linearly separable from the other 2; the\nlatter are NOT linearly separable from each other.\n\n.. topic:: References\n\n   - Fisher, R.A. "The use of mul
tiple measurements in taxonomic problems"\n     Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to\n     Mathematical Statistics" (John Wiley, NY, 1950).\n   - Duda, R.O., & Hart, P.E. (1973) Patter
n Classification and Scene Analysis.\n     (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.\n   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System\n     Structure and Classification
Rule for Recognition in Partially Exposed\n     Environments".  IEEE Transactions on Pattern Analysis and Machine\n     Intelligence, Vol. PAMI-2, No. 1, 67-71.\n   - Gates, G.W. (1972) "The Reduced Nearest Neighbor Ru
le".  IEEE Transactions\n     on Information Theory, May 1972, 431-433.\n   - See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II\n     conceptual clustering system finds 3 classes in the data.\n   -
Many, many more ...',
 'feature_names': ['sepal length (cm)',
  'sepal width (cm)',
  'petal length (cm)',
  'petal width (cm)'],
 'filename': 'iris.csv',
 'data_module': 'sklearn.datasets.data'}
```

Observation :

- We have a dictionary which contains data and information dataset.

Explore dataset

In [4]:
```python
dataset.keys()
```

Out[4]:
```
dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names', 'filename', 'data_module'])
```

Observation :

- 'DESCR' contains the description of the dataset.
- 'target_names' contains dependent feature name and it's data is present inside 'target'.
- 'feature_names' contains independent feature name and it's data is present inside 'data'.

In [5]:
```python
# We will check the description of dataset
print(dataset['DESCR'])
```

```
.. _iris_dataset:

Iris plants dataset
--------------------

**Data Set Characteristics:**

    :Number of Instances: 150 (50 in each of three classes)
    :Number of Attributes: 4 numeric, predictive attributes and the class
    :Attribute Information:
        - sepal length in cm
        - sepal width in cm
        - petal length in cm
        - petal width in cm
        - class:
                - Iris-Setosa
                - Iris-Versicolour
                - Iris-Virginica

    :Summary Statistics:

    ============== ==== ==== ======= ===== ====================
                    Min  Max   Mean    SD   Class Correlation
    ============== ==== ==== ======= ===== ====================
    sepal length:   4.3  7.9   5.84   0.83    0.7826
    sepal width:    2.0  4.4   3.05   0.43   -0.4194
    petal length:   1.0  6.9   3.76   1.76    0.9490  (high!)
    petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)
    ============== ==== ==== ======= ===== ====================

    :Missing Attribute Values: None
    :Class Distribution: 33.3% for each of 3 classes.
    :Creator: R.A. Fisher
    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
    :Date: July, 1988

The famous Iris database, first used by Sir R.A. Fisher. The dataset is taken
from Fisher's paper. Note that it's the same as in R, but not as in the UCI
Machine Learning Repository, which has two wrong data points.

This is perhaps the best known database to be found in the
pattern recognition literature.  Fisher's paper is a classic in the field and
is referenced frequently to this day.  (See Duda & Hart, for example.)  The
data set contains 3 classes of 50 instances each, where each class refers to a
type of iris plant.  One class is linearly separable from the other 2; the
latter are NOT linearly separable from each other.

.. topic:: References

   - Fisher, R.A. "The use of multiple measurements in taxonomic problems"
     Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to
     Mathematical Statistics" (John Wiley, NY, 1950).
   - Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analysis.
     (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.
   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System
     Structure and Classification Rule for Recognition in Partially Exposed
     Environments".  IEEE Transactions on Pattern Analysis and Machine
     Intelligence, Vol. PAMI-2, No. 1, 67-71.
   - Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEEE Transactions
     on Information Theory, May 1972, 431-433.
   - See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II
     conceptual clustering system finds 3 classes in the data.
   - Many, many more ...
```

Create dataframe

In [6]:
```python
import pandas as pd
import numpy as np
```

In [7]:
```python
df = pd.DataFrame(dataset['data'],columns = dataset['feature_names'])
df.head()
```

Out[7]:

	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 [8]:
```python
# target data is loaded into dataframe
df['target'] = dataset['target']

df.head()
```

Out[8]:

	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 [9]:
```python
df.shape
```

Out[9]:
```
(150, 5)
```

In [10]:
```python
df['target'].unique()
```

Out[10]:
```
array([0, 1, 2])
```

Observation :

- As we are doing binary classification problem we need 2 target values but we have 3 target values.So, we take only 2 values and remove 1 value i.e here we will remove '2'.

In [11]:
```python
df['target'] != 2
```

Out[11]:
```
0       True
1       True
2       True
3       True
4       True
       ...
145    False
146    False
147    False
148    False
149    False
Name: target, Length: 150, dtype: bool
```

In [12]:
```python
# removing records whose target value is 2
df_copy = df[df['target'] != 2]

df_copy.head()
```

Out[12]:

	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 [14]:
```python
df_copy['target'].unique()
```

Out[14]:
```
array([0, 1])
```

In [15]:
```python
df_copy.shape
```

Out[15]:
```
(100, 5)
```

---

1. Separating independent and dependent feature

In [16]:
```python
x = df_copy.iloc[:,:-1]

y = df_copy.iloc[:,-1]
```

In [17]:
```python
print(x)
print()
print(y)
```

```
    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
..                ...               ...                ...               ...
95                5.7               3.0                4.2               1.2
96                5.7               2.9                4.2               1.3
97                6.2               2.9                4.3               1.3
98                5.1               2.5                3.0               1.1
99                5.7               2.8                4.1               1.3

[100 rows x 4 columns]

0     0
1     0
2     0
3     0
4     0
     ..
95    1
96    1
97    1
98    1
99    1
Name: target, Length: 100, dtype: int32
```

---

2. Train Test Split of data

In [18]:
```python
from sklearn.model_selection import train_test_split
```

In [19]:
```python
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size = 0.2,random_state = 42)
```

In [20]:
```python
print('Length of our dataset is',len(df_copy))

print('Length of our train data is',len(x_train))
# Test data is 20% of actual data
print('Length of our test datat is',len(x_test))
```

```
Length of our dataset is 100
Length of our train data is 80
Length of our test datat is 20
```

---

3. Model Training

In [21]:
```python
from sklearn.linear_model import LogisticRegression
```

In [22]:
```python
# intially let's not consider any parameters
classification = LogisticRegression()

classification
```

Out[22]:
```
LogisticRegression()
```

In [23]:
```python
classification.fit(x_train,y_train)
```

Out[23]:
```
LogisticRegression()
```

---

4. Predication

In [24]:
```python
y_pred = classification.predict(x_test)

y_pred
```

Out[24]:
```
array([1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0])
```

---

5. Confusion Metrics, Accuracy, Classification Report

In [25]:
```python
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
```

In [26]:
```python
# y_test is actual data
# y_pred is predicated data

print('Confusion Metrics :')
print(confusion_matrix(y_test,y_pred))
```

```
Confusion Metrics :
[[12  0]
 [ 0  8]]
```

Observation :

- As FP and FN is 0 it is a very good model.

In [27]:
```python
accuracy = accuracy_score(y_test,y_pred) * 100
print(f'Accuracy : {accuracy} %')
```

```
Accuracy : 100.0 %
```

Observation :

- As FP and FN is 0 Accuracy is 100%

In [28]:
```python
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        12
           1       1.00      1.00      1.00         8

    accuracy                           1.00        20
   macro avg       1.00      1.00      1.00        20
weighted avg       1.00      1.00      1.00        20
```

Cross Validation

CV is done by dividing training data internally into training and validation data and calculate accuracy

Now, We have to apply logistic regression with cross validation and obtain multiple accuracy within the triaining data by spliting training data into training data and validation data.

In [29]:
```python
from sklearn.model_selection import KFold
```

In [30]:
```python
# by default number of split is 5
cv = KFold()

cv
```

Out[30]:
```
KFold(n_splits=5, random_state=None, shuffle=False)
```

Observation :

- Cross Validation number of spilt will be 5.

In [31]:
```python
from sklearn.model_selection import cross_val_score
```

In [32]:
```python
# there are the scores all the cross validation
cv_scores = cross_val_score(classification,x_train,y_train,scoring = 'accuracy',cv = cv)

cv_scores
```

Out[32]:
```
array([1., 1., 1., 1., 1.])
```

Observation :

- Here, for cros_value_score we give 'clasification' estimator then tell model to split data internally into train and validation using x_train , y_train then accuracy scoring is need then number of split is told by cv.

In [34]:
```python
final_score = np.mean(cv_scores)

# Now, we got the final cross validation score by doing average of cross validatino score
final_score
```

Out[34]:
```
1.0
```

One more example on Cross Validation

In [35]:
```python
## Lets see more complex data

# make a prediction with a multinomial logistic regression model
from sklearn.datasets import make_classification
from sklearn.linear_model import LogisticRegression

# define dataset
X, y = make_classification(n_samples=1000, n_features=10, n_informative=5, n_redundant=5, n_classes=2, random_state=1)
```

In [36]:
```python
X,y
```

Out[36]:
```
(array([[ 2.56999479, -0.13019997,  3.16075093, ..., -1.93094078,
          3.26130366,  2.05692145],
        [ 0.34129317,  2.51321418, -0.80416572, ...,  6.24734437,
         -1.92769365,  2.9503149 ],
        [ 2.27539972,  3.36561455,  0.17164362, ...,  2.74693781,
          0.13492444,  2.00339547],
        ...,
        [ 0.5234359 ,  1.90466429,  0.93243365, ...,  1.53945231,
          1.90646166,  1.99458587],
        [ 1.33747921,  3.25859684,  0.78792366, ...,  5.18788314,
         -0.82071083,  3.51411431],
        [-0.98534299,  0.83919047,  2.5820803 , ...,  3.04705685,
          0.66885641,  3.32838496]]),
 array([1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1,
        1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1,
        0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0,
        1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0,
        0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0,
        1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0,
        0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1,
        1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0,
        1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0,
        1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0,
        0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1,
        0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0,
        1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0,
        0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1,
        0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1,
        0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0,
        0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0,
        1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1,
        1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0,
        1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1,
        0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0,
        0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1,
        1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1,
        1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0,
        1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0,
        1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1,
        0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0,
        1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0,
        1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1,
        1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1,
        1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1,
        0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0,
        1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0,
        1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0,
        0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0,
        0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0,
        1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0,
        0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0,
        0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1,
        1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1,
        1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1,
        0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0,
        0, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1,
        1, 0, 0, 0, 0, 1, 1, 0, 0, 0]))
```

In [37]:
```python
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42)
```

In [38]:
```python
complex_class_model = LogisticRegression(max_iter = 200)
# model training
complex_class_model.fit(X_train,y_train)
```

Out[38]:
```
LogisticRegression(max_iter=200)
```

In [39]:
```python
y_pred_complex = complex_class_model.predict(X_test)
# prediction
y_pred_complex
```

Out[39]:
```
array([0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0,
       0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0,
       1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0,
       0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0,
       0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0,
       1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0,
       0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1,
       0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1,
       0, 1])
```

In [40]:
```python
print(confusion_matrix(y_test,y_pred_complex))
print(accuracy_score(y_test,y_pred_complex))
print(classification_report(y_test,y_pred_complex))
```

```
[[78 13]
 [29 80]]
0.79
              precision    recall  f1-score   support

           0       0.73      0.86      0.79        91
           1       0.86      0.73      0.79       109

    accuracy                           0.79       200
   macro avg       0.79      0.80      0.79       200
weighted avg       0.80      0.79      0.79       200
```

Observation :

- Here, we can see that there are more errors and accuracy is less i.e 79.

In [41]:
```python
# Now, Can we improve accuracy using cross validation

cv = KFold(n_splits = 5)
cv_scores = cross_val_score(complex_class_model,X_train,y_train,scoring = 'accuracy',cv = cv)

cv_scores
```

Out[41]:
```
array([0.80625, 0.78125, 0.79375, 0.8125 , 0.85625])
```

In [42]:
```python
# mean of cross validation scores
final_scores = np.mean(cv_scores)

final_scores
```

Out[42]:
```
0.8099999999999999
```

Observation :

- For stack holder we have to tell we have got accuracy of maximum of 85% and minimum of 78%. We should avoid telling 80% is accuracy not a single value.

Further this cross validation can be used to get best parameters

---