→ Classification Logistic Regression

40 71000]

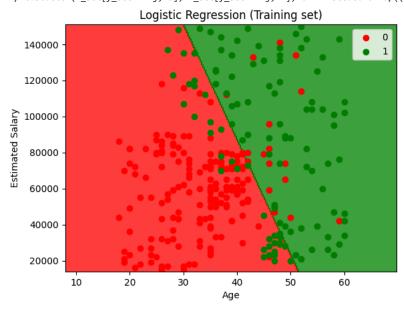
```
1 # Importing the libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd
1 # Importing the dataset
2 dataset = pd.read_csv(r'/content/drive/MyDrive/Social_Network_Ads.csv')
3 X = dataset.iloc[:, :-1].values
4 y = dataset.iloc[:, -1].values
Double-click (or enter) to edit
1 from google.colab import drive
2 drive.mount('/content/drive')
    Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
1 # Splitting the dataset into the Training set and Test set
2 from sklearn.model_selection import train_test_split
3 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)
4 print(X_train)
5 print(y_train)
6 print(X_test)
7 print(y_test)
          33 69000]
           20 82000]
          31 74000]
          42 80000]
          35 72000]
          33 149000]
```

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ו אסאדי דצ
          43 1290001
         59 76000]
          18 44000]
          36 118000]
          42 900001
          47 30000]
          26
             43000]
          40 780001
          46 59000]
          59
             420001
1 # Feature Scaling
2 from sklearn.preprocessing import StandardScaler
3 sc = StandardScaler()
4 X_train = sc.fit_transform(X_train)
5 X_test = sc.transform(X_test)
6 print(X_train)
7 print(X_test)
    [[ 0.58164944 -0.88670699]
     [-0.60673761 1.46173768]
     [-0.01254409 -0.5677824 ]
     [-0.60673761 1.89663484]
     [ 1.37390747 -1.40858358]
     [ 1.47293972 0.99784738]
     [ 0.08648817 -0.79972756]
     [-0.01254409 -0.24885782]
     [-0.21060859 -0.5677824 ]
     [-0.21060859 -0.19087153]
     [-0.30964085 -1.29261101]
     [-0.30964085 -0.5677824 ]
     [ 0.38358493  0.09905991]
      0.8787462 -0.59677555]
     [ 2.06713324 -1.17663843]
      1.07681071 -0.13288524]
     [ 0.68068169 1.78066227]
     [-0.70576986 0.56295021]
     [ 0.77971394  0.35999821]
     [ 0.8787462 -0.53878926]
     [-1.20093113 -1.58254245]
     [ 2.1661655  0.93986109]
     [-0.01254409 1.22979253]
     [ 0.18552042    1.08482681]
     [ 0.38358493 -0.48080297]
     [-0.30964085 -0.30684411]
     [ 0.97777845 -0.8287207 ]
      0.97777845 1.8676417 ]
     [-0.01254409 1.25878567]
     [-0.90383437 2.27354572]
     [-1.20093113 -1.58254245]
     [ 2.1661655 -0.79972756]
     [-1.39899564 -1.46656987]
     [ 0.38358493  2.30253886]
     [ 0.77971394  0.76590222]
     [-1.00286662 -0.30684411]
     [ 0.08648817 0.76590222]
     [-1.00286662 0.56295021]
     [ 0.28455268  0.07006676]
     [ 0.68068169 -1.26361786]
     [-0.50770535 -0.01691267]
     [-1.79512465 0.35999821]
     [-0.70576986 0.12805305]
     [ 0.38358493  0.30201192]
     [-0.30964085 0.07006676]
     [-0.50770535 2.30253886]
     [ 0.18552042  0.04107362]
     [ 1.27487521 2.21555943]
     [ 0.77971394  0.27301877]
     [-0.30964085 0.1570462 ]
     [-0.01254409 -0.53878926]
     [-0.21060859 0.1570462 ]
     [-0.11157634 0.24402563]
     [-0.01254409 -0.24885782]
     [ 2.1661655   1.11381995]
     [-1.79512465 0.35999821]
     [ 1.86906873 0.12805305]
     [ 0.38358493 -0.13288524]
```

```
1 # Training the Logistic Regression model on the Training set
2 from sklearn.linear_model import LogisticRegression
3 classifier = LogisticRegression(random_state = 0)
4 classifier.fit(X_train, y_train)
             LogisticRegression
    LogisticRegression(random_state=0)
1 # Predicting a new result
2 print(classifier.predict(sc.transform([[30,87000]])))
    [0]
1 # Predicting the Test set results
2 y_pred = classifier.predict(X_test)
 \texttt{3 print(np.concatenate((y\_pred.reshape(len(y\_pred),1), y\_test.reshape(len(y\_test),1)),1))} \\
    [[0 0]
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     [1 1]
     [0 1]
     [0 0]
     [0 0]
```

```
1 # Making the Confusion Matrix
 2 from sklearn.metrics import confusion_matrix, accuracy_score
3 cm = confusion_matrix(y_test, y_pred)
4 print(cm)
5 accuracy_score(y_test, y_pred)
     [[65 3]
     [ 8 24]]
     0.89
1 # Visualising the Training set results
2 from matplotlib.colors import ListedColormap
 3 X_set, y_set = sc.inverse_transform(X_train), y_train
4 \text{ X1, X2} = \text{np.meshgrid(np.arange(start = X\_set[:, 0].min() - 10, stop = X\_set[:, 0].max() + 10, step = 0.25),}
                       np.arange(start = X_set[:, 1].min() - 1000, stop = X_set[:, 1].max() + 1000, step = 0.25))
6 plt.contourf(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel(), X2.ravel()]).T)).reshape(X1.shape),
               alpha = 0.75, cmap = ListedColormap(('red', 'green')))
8 plt.xlim(X1.min(), X1.max())
9 plt.ylim(X2.min(), X2.max())
10 for i, j in enumerate(np.unique(y_set)):
      plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)
12 plt.title('Logistic Regression (Training set)')
13 plt.xlabel('Age')
14 plt.ylabel('Estimated Salary')
15 plt.legend()
16 plt.show()
```

<ipython-input-14-73b57679e135>:11: UserWarning: *c* argument looks like a single numeri
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'gr



```
1 # Visualising the Test set results
 2 from matplotlib.colors import ListedColormap
 3 X_set, y_set = sc.inverse_transform(X_test), y_test
 4 \text{ X1, X2} = \text{np.meshgrid(np.arange(start = X\_set[:, 0].min() - 10, stop = X\_set[:, 0].max() + 10, step = 0.25),}
                        np.arange(start = X_set[:, 1].min() - 1000, stop = X_set[:, 1].max() + 1000, stop = 0.25))
  6 \ plt.contourf(X1, \ X2, \ classifier.predict(sc.transform(np.array([X1.ravel()], \ X2.ravel()]).T)).reshape(X1.shape), 
                alpha = 0.75, cmap = ListedColormap(('red', 'green')))
 8 plt.xlim(X1.min(), X1.max())
 9 plt.ylim(X2.min(), X2.max())
10 for i, j in enumerate(np.unique(y_set)):
      plt.scatter(X\_set[y\_set == j, 0], X\_set[y\_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)
12 plt.title('Logistic Regression (Test set)')
13 plt.xlabel('Age')
14 plt.ylabel('Estimated Salary')
15 plt.legend()
16 plt.show()
```

<ipython-input-15-4a24fc64ffb4>:11: UserWarning: *c* argument looks like a single numeri
plt.scatter($X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'gr'))$

Logistic Regression (Test set) 0 140000 1 120000 Estimated Salary 100000 80000 60000 40000 20000 20 50 10 30 40 60 Age

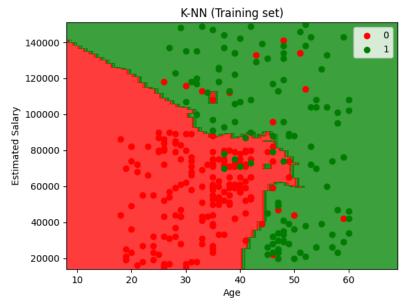
K -N N -- Classification K nearest neigbour

```
1 # Training the K-NN model on the Training set
\hbox{2 from sklearn.} \\ \text{neighbors import KNeighborsClassifier}
3 classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
4 classifier.fit(X_train, y_train)
     ▼ KNeighborsClassifier
     KNeighborsClassifier()
1 # Predicting a new result
2 print(classifier.predict(sc.transform([[30,87000]])))
    [0]
1 # Predicting the Test set results
2 y_pred = classifier.predict(X_test)
3 print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
    [[0 0]]
     [0 0]
     [0 0]
     [0 0]
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     [1 1]
     [0 0]
     [0 0]
```

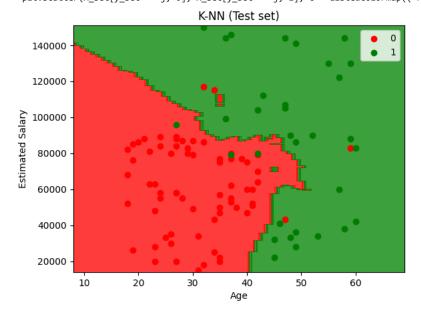
```
11/04/2024, 23:48
```

```
[0 0]
           [0 0]
           [0 0]
            [0 1]
           [1 1]
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            [0 0]
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           [1 0]
           [1 1]
           [1 1]
           [0 0]
  1 # Making the Confusion Matrix
  2 from sklearn.metrics import confusion_matrix, accuracy_score
  3 cm = confusion_matrix(y_test, y_pred)
 4 print(cm)
  5 accuracy_score(y_test, y_pred)
         [[64 4]
           [ 3 29]]
         0.93
  1 from matplotlib.colors import ListedColormap
  2 X_set, y_set = sc.inverse_transform(X_train), y_train
 3 \ X1, \ X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 10, \ stop = X_set[:, 0].max() + 10, \ step = 1),
  4
                                              np.arange(start = X_set[:, 1].min() - 1000, stop = X_set[:, 1].max() + 1000, step = 1))
 \label{eq:contourf} 5 \ \text{plt.contourf}(X1, \ X2, \ \text{classifier.predict}(\text{sc.transform}(\text{np.array}([X1.ravel(), \ X2.ravel()]).T)).\\ \text{reshape}(X1.\text{shape}), \ X2.\text{ravel}()) \\ \text{sc.transform}(\text{np.array}([X1.ravel(), \ X2.ravel()]).T)).\\ \text{reshape}(X1.\text{shape}), \ X3.\text{ravel}()) \\ \text{sc.transform}(\text{np.array}([X1.ravel(), \ X3.ravel()]).T)).\\ \text{reshape}(X1.\text{shape}), \ X3.\text{ravel}()) \\ \text{sc.transform}(\text{np.array}([X1.ravel(), \ X3.ravel()])).\\ \text{sc.transform}(\text{np.array}([X1.ravel(), \ X3.ravel()])).\\ \text{sc.transform}(\text{np.array}([X1.ravel(), \ X3.ravel()])).\\ \text{sc.transform}(\text{np.array}([X1.ravel(), \ X3.ravel()])).\\ \text{sc.transform}(\text{np.array}([X1.ravel(), \ X3.ravel()])).
  6
                              alpha = 0.75, cmap = ListedColormap(('red', 'green')))
 7 plt.xlim(X1.min(), X1.max())
  8 plt.ylim(X2.min(), X2.max())
 9 for i, j in enumerate(np.unique(y_set)):
            plt.scatter(X\_set[y\_set == j, 0], X\_set[y\_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)
10
11 plt.title('K-NN (Training set)')
12 plt.xlabel('Age')
13 plt.ylabel('Estimated Salary')
14 plt.legend()
15 plt.show()
```

<ipython-input-20-9061e2cf8fe3>:10: UserWarning: *c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)



<ipython-input-21-8ae8de7a7cff>:11: UserWarning: *c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)



 ${\bf 1} \ {\rm Start} \ {\rm coding} \ {\rm or} \ {\rm \underline{generate}} \ {\rm with} \ {\rm AI.}$

Support Vector Machine (SVM) Algorthim

```
1 # Importing the libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd
1 # Importing the dataset
2 dataset = pd.read_csv(r'/content/drive/MyDrive/Social_Network_Ads.csv')
3 X = dataset.iloc[:, :-1].values
4 y = dataset.iloc[:, -1].values
1 # Training the SVM model on the Training set
2 from sklearn.svm import SVC
3 classifier = SVC(kernel = 'linear', random_state = 0)
4 classifier.fit(X_train, y_train)
                       SVC
    SVC(kernel='linear', random_state=0)
1 # Predicting a new result
2 print(classifier.predict(sc.transform([[30,87000]])))
    [0]
1 # Predicting the Test set results
2 y_pred = classifier.predict(X_test)
 \texttt{3 print(np.concatenate((y\_pred.reshape(len(y\_pred),1), y\_test.reshape(len(y\_test),1)),1))} \\
    [[0 0]
     [0 0]
     [0 0]
     [0 0]
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     [1 1]
     [0 0]
     [0 0]
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     [1 1]
```

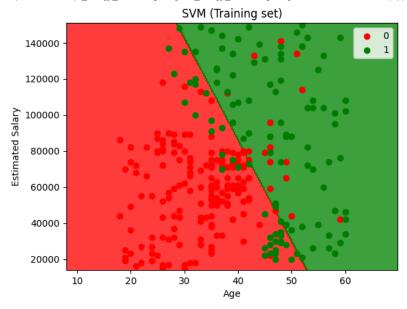
```
[0 0]
[1 1]
[0 0]
[1 1]
[1 0]
[0 0]
[0 0]
[0 1]
[0 1]
[0 0]
[0 0]
```

```
1 # Making the Confusion Matrix
2 from sklearn.metrics import confusion_matrix, accuracy_score
3 cm = confusion_matrix(y_test, y_pred)
4 print(cm)
5 accuracy_score(y_test, y_pred)

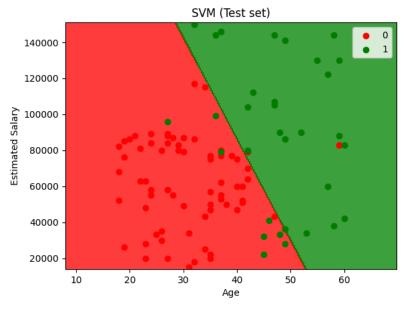
[[66 2]
   [8 24]]
   0.9
```

```
1 # Visualising the Training set results
 2 from matplotlib.colors import ListedColormap
 3 X_set, y_set = sc.inverse_transform(X_train), y_train
 4 X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 10, stop = X_set[:, 0].max() + 10, step = 0.25),
                        np.arange(start = X_set[:, 1].min() - 1000, stop = X_set[:, 1].max() + 1000, stop = 0.25))
 \label{eq:contourf} \texttt{(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel()], X2.ravel()]).T)).reshape(X1.shape),} \\
                alpha = 0.75, cmap = ListedColormap(('red', 'green')))
 8 plt.xlim(X1.min(), X1.max())
9 plt.ylim(X2.min(), X2.max())
10 for i, j in enumerate(np.unique(y_set)):
      plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)
11
12 plt.title('SVM (Training set)')
13 plt.xlabel('Age')
14 plt.ylabel('Estimated Salary')
15 plt.legend()
16 plt.show()
```

<ipython-input-28-501d2325cffa>:11: UserWarning: *c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)



<ipython-input-29-8c7ca6815161>:11: UserWarning: *c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)



Kernel SVM

```
1 # Importing the libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd
1 # Importing the dataset
2 dataset = pd.read_csv('Social_Network_Ads.csv')
3 X = dataset.iloc[:, :-1].values
4 y = dataset.iloc[:, -1].values
1 # Splitting the dataset into the Training set and Test set
2 from sklearn.model_selection import train_test_split
3 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)
4 print(X_train)
5 print(y_train)
6 print(X_test)
7 print(y_test)
          44 39000]
    [[
          32 120000]
          38 500001
          32 135000]
          52 21000]
          53 104000]
          39
             420001
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              61000]
          36
              50000]
              630001
          36
```

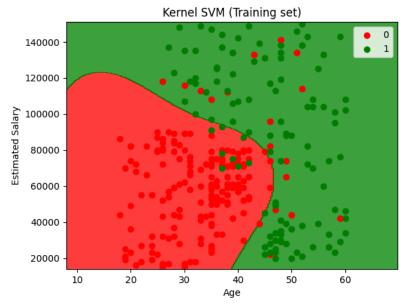
```
25000]
         35
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         59 29000]
         49 650001
         45 131000]
         31 89000]
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             51000]
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         38 112000]
          40 107000]
         42 53000]
         35 590001
         48 41000]
          48 134000]
         38 113000]
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         42 650001
1 # Feature Scaling
2 from sklearn.preprocessing import StandardScaler
3 sc = StandardScaler()
4 X_train = sc.fit_transform(X_train)
5 X_test = sc.transform(X_test)
6 print(X_train)
7 print(X_test)
   [[ 0.58164944 -0.88670699]
     [-0.60673761 1.46173768]
     [-0.01254409 -0.5677824 ]
    [-0.60673761 1.89663484]
     [ 1.37390747 -1.40858358]
    [ 1.47293972 0.99784738]
    [ 0.08648817 -0.79972756]
     [-0.01254409 -0.24885782]
     [-0.21060859 -0.5677824 ]
    [-0.21060859 -0.19087153]
     [-0.30964085 -1.29261101]
     [-0.30964085 -0.5677824 ]
     [ 0.38358493  0.09905991]
     [ 0.8787462 -0.59677555]
     [ 2.06713324 -1.17663843]
     [ 1.07681071 -0.13288524]
      0.68068169 1.78066227]
     [-0.70576986 0.56295021]
      0.77971394 0.35999821]
     [ 0.8787462 -0.53878926]
    [-1.20093113 -1.58254245]
     [ 2.1661655  0.93986109]
     [-0.01254409 1.22979253]
      0.18552042 1.08482681]
      0.38358493 -0.48080297]
     [-0.30964085 -0.30684411]
    [ 0.97777845 -0.8287207 ]
```

[0 0] [0 0]

```
[ 0.97777845 1.8676417 ]
     [-0.01254409 1.25878567]
     [-0.90383437 2.27354572]
     [-1.20093113 -1.58254245]
     [ 2.1661655 -0.79972756]
     [-1.39899564 -1.46656987]
     [ 0.38358493  2.30253886]
     [ 0.77971394  0.76590222]
     [-1.00286662 -0.30684411]
     [ 0.08648817  0.76590222]
     [-1.00286662 0.56295021]
     [ 0.28455268  0.07006676]
     [ 0.68068169 -1.26361786]
     [-0.50770535 -0.01691267]
     [-1.79512465 0.35999821]
     [-0.70576986 0.12805305]
     [ 0.38358493  0.30201192]
     [-0.30964085 0.07006676]
     [-0.50770535 2.30253886]
     [ 0.18552042  0.04107362]
       1.27487521 2.21555943]
     [ 0.77971394  0.27301877]
     [-0.30964085 0.1570462 ]
     [-0.01254409 -0.53878926]
     [-0.21060859 0.1570462 ]
     [-0.11157634 0.24402563]
     [-0.01254409 -0.24885782]
     [ 2.1661655    1.11381995]
     [-1.79512465 0.35999821]
     [ 1.86906873 0.12805305]
     [ 0.38358493 -0.13288524]
1 # Training the Kernel SVM model on the Training set
2 from sklearn.svm import SVC
3 classifier = SVC(kernel = 'rbf', random_state = 0)
4 classifier.fit(X_train, y_train)
             SVC
    SVC(random_state=0)
1 # Predicting a new result
2 print(classifier.predict(sc.transform([[30,87000]])))
    [0]
1 \# Predicting the Test set results
2 y_pred = classifier.predict(X_test)
3 print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
    [[0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [1 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [1 0]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [1 1]
     [0 0]
     [1 1]
     [0 0]
     [0 0]
     [0 0]
```

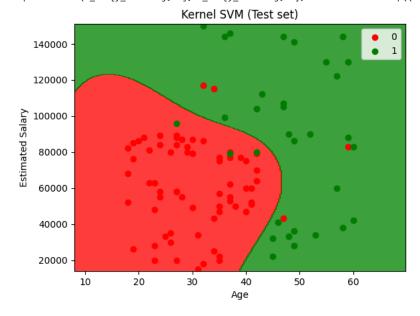
```
[0 1]
      [1 1]
      [0 0]
      [0 0]
      [0 0]
      [0 0]
      [0 0]
      [0 0]
      [1 1]
      [0 0]
      [0 0]
      [0 0]
      [0 0]
      [1 1]
      [0 0]
      [0 0]
      [1 1]
      [0 0]
      [1 1]
      [1 1]
      [0 0]
      [0 0]
      [1 0]
      [1 1]
      [1 1]
      [0 0]
      [0 0]
 1 # Making the Confusion Matrix
 2 from sklearn.metrics import confusion_matrix, accuracy_score
3 cm = confusion_matrix(y_test, y_pred)
 4 print(cm)
 5 accuracy_score(y_test, y_pred)
     [[64 4]
     [ 3 29]]
     0.93
1 # Visualising the Training set results
 2 from matplotlib.colors import ListedColormap
 3 X_set, y_set = sc.inverse_transform(X_train), y_train
4 \ X1, \ X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 10, \ stop = X_set[:, 0].max() + 10, \ step = 0.25),
                        np.arange(start = X_set[:, 1].min() - 1000, stop = X_set[:, 1].max() + 1000, step = 0.25))
 6 plt.contourf(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel(), X2.ravel()]).T)).reshape(X1.shape),
                alpha = 0.75, cmap = ListedColormap(('red', 'green')))
 8 plt.xlim(X1.min(), X1.max())
9 plt.ylim(X2.min(), X2.max())
10 for i, j in enumerate(np.unique(y_set)):
      plt.scatter(X\_set[y\_set == j, \ 0], \ X\_set[y\_set == j, \ 1], \ c = ListedColormap(('red', \ 'green'))(i), \ label = j)
12 plt.title('Kernel SVM (Training set)')
13 plt.xlabel('Age')
14 plt.ylabel('Estimated Salary')
15 plt.legend()
16 plt.show()
```

<ipython-input-9-e13552a9f4e8>:11: UserWarning: *c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided a
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)



```
1 \# Visualising the Test set results
 2 from matplotlib.colors import ListedColormap
 3 X_set, y_set = sc.inverse_transform(X_test), y_test
 4 \; X1, \; X2 = np.meshgrid(np.arange(start = X_set[:, \, \emptyset].min() \, - \, 10, \; stop = X_set[:, \, \, \emptyset].max() \, + \, 10, \; step = \, 0.25),
                         np.arange(start = X\_set[:, 1].min() - 1000, stop = X\_set[:, 1].max() + 1000, stop = 0.25))
 6 plt.contourf(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel(), X2.ravel()]).T)).reshape(X1.shape),
                alpha = 0.75, cmap = ListedColormap(('red', 'green')))
 8 plt.xlim(X1.min(), X1.max())
 9 plt.ylim(X2.min(), X2.max())
10 for i, j in enumerate(np.unique(y_set)):
       plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)
12 plt.title('Kernel SVM (Test set)')
13 plt.xlabel('Age')
14 plt.ylabel('Estimated Salary')
15 plt.legend()
16 plt.show()
```

<ipython-input-10-6fe3d2c99629>:11: UserWarning: *c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)



Naive Bayes Algorithm

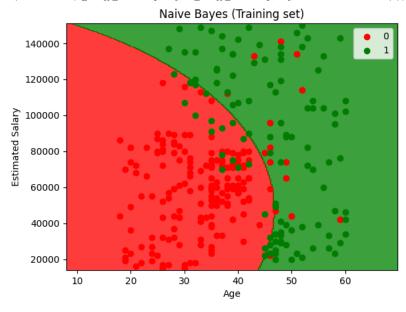
```
1 # Importing the libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd
1 # Importing the dataset
2 dataset = pd.read_csv('Social_Network_Ads.csv')
3 X = dataset.iloc[:, :-1].values
4 y = dataset.iloc[:, -1].values
1 # Splitting the dataset into the Training set and Test set
2 from sklearn.model_selection import train_test_split
3 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)
4 print(X_train)
5 print(y_train)
6 print(X_test)
7 print(y_test)
         44 39000]
    ]]
         32 120000]
          38 50000]
         32 135000]
         52 210001
         53 104000]
         39 42000]
             61000]
         38
         36
             50000]
         36 63000]
         35
             25000]
         35
             500001
         42 73000]
         47
             49000]
         59 29000]
         49 650001
         45 131000]
         31 89000]
         46 820001
         47 51000]
         26 15000]
         60 102000]
         38 112000]
         40 107000]
         42 53000]
         35 590001
         48 41000]
         48 134000]
         38 1130001
         29 148000]
          26 15000]
         60 42000]
         24 19000]
         42 149000]
         46 96000]
             59000]
         28
             96000]
         39
         28
             89000]
         41
             72000]
             26000]
         45
         33
             69000]
             82000]
         20
             740001
         31
         42
             80000]
             72000]
         33 149000]
         40 71000]
         51 146000]
         46 79000]
         35
             750001
         38
             51000]
             75000]
         37
             78000]
         38
             61000]
         60 108000]
         20
             82000]
         57 740001
         42 65000]
```

```
1 # Feature Scaling
2 from sklearn.preprocessing import StandardScaler
3 sc = StandardScaler()
4 X_train = sc.fit_transform(X_train)
5 X_test = sc.transform(X_test)
6 print(X_train)
7 print(X_test)
    [[ 0.58164944 -0.88670699]
      -0.60673761 1.46173768]
    [-0.01254409 -0.5677824 ]
     [-0.60673761 1.89663484]
     [ 1.37390747 -1.40858358]
     [ 1.47293972 0.99784738]
     [ 0.08648817 -0.79972756]
     [-0.01254409 -0.24885782]
    [-0.21060859 -0.5677824 ]
     [-0.21060859 -0.19087153]
     [-0.30964085 -1.29261101]
     [-0.30964085 -0.5677824 ]
    [ 0.38358493  0.09905991]
     [ 0.8787462 -0.59677555]
     [ 2.06713324 -1.17663843]
     [ 1.07681071 -0.13288524]
     [ 0.68068169 1.78066227]
     [-0.70576986 0.56295021]
     [ 0.77971394 0.35999821]
     [ 0.8787462 -0.53878926]
     [-1.20093113 -1.58254245]
     [ 2.1661655 0.93986109]
     [-0.01254409 1.22979253]
     0.38358493 -0.48080297]
     [-0.30964085 -0.30684411]
     [ 0.97777845 -0.8287207 ]
     [ 0.97777845 1.8676417 ]
     [-0.01254409 1.25878567]
     [-0.90383437 2.27354572]
     [-1.20093113 -1.58254245]
     [ 2.1661655 -0.79972756]
     [-1.39899564 -1.46656987]
     [ 0.77971394  0.76590222]
     [-1.00286662 -0.30684411]
    [ 0.08648817  0.76590222]
     [-1.00286662 0.56295021]
      0.28455268 0.07006676]
      0.68068169 -1.26361786]
     [-0.50770535 -0.01691267]
     [-1.79512465 0.35999821]
    [-0.70576986 0.12805305]
     [ 0.38358493  0.30201192]
     [-0.30964085 0.07006676]
     [-0.50770535 2.30253886]
    [ 0.18552042  0.04107362]
     [ 1.27487521 2.21555943]
     [ 0.77971394  0.27301877]
     [-0.30964085 0.1570462 ]
    [-0.01254409 -0.53878926]
     [-0.21060859 0.1570462 ]
     [-0.11157634 0.24402563]
    [-0.01254409 -0.24885782]
     [-1.79512465 0.35999821]
     [ 1.86906873 0.12805305]
     [ 0.38358493 -0.13288524]
1 # Training the Naive Bayes model on the Training set
2 from sklearn.naive_bayes import GaussianNB
3 classifier=GaussianNB ()
4 classifier.fit(X_train, y_train)
    ▼ GaussianNB
    GaussianNB()
1 # Predicting a new result
2 print(classifier.predict(sc.transform([[30,87000]])))
    [0]
```

```
1 # Predicting the Test set results
2 y_pred = classifier.predict(X_test)
3 print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
    [[0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [1 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [1 1]
     [0 0]
     [1 1]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 1]
     [1 1]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [1 1]
     [1 1]
     [0 0]
     [0 0]
     [1 0]
     [1 1]
     [0 1]
     [0 0]
     [0 0]
1 # Making the Confusion Matrix
2 from sklearn.metrics import confusion_matrix, accuracy_score
3 cm = confusion_matrix(y_test, y_pred)
4 print(cm)
5 accuracy_score(y_test, y_pred)
    [[65 3]
    [ 7 25]]
    0.9
```

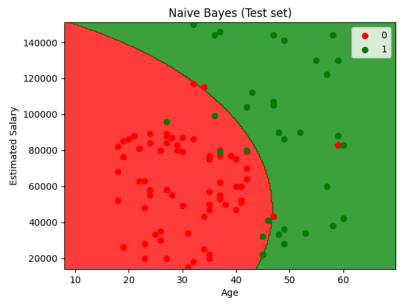
```
1 # Visualising the Training set results
 2 from matplotlib.colors import ListedColormap
3 X_set, y_set = sc.inverse_transform(X_train), y_train
4 X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 10, stop = X_set[:, 0].max() + 10, step = 0.25),
                        np.arange(start = X\_set[:, 1].min() - 1000, stop = X\_set[:, 1].max() + 1000, stop = 0.25))
6 plt.contourf(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel(), X2.ravel()]).T)).reshape(X1.shape),
               alpha = 0.75, cmap = ListedColormap(('red', 'green')))
8 plt.xlim(X1.min(), X1.max())
9 plt.ylim(X2.min(), X2.max())
10 for i, j in enumerate(np.unique(y_set)):
      plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)
12 plt.title('Naive Bayes (Training set)')
13 plt.xlabel('Age')
14 plt.ylabel('Estimated Salary')
15 plt.legend()
16 plt.show()
```

<ipython-input-9-a3458d358c6d>:11: UserWarning: *c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided a
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)



```
1 # Visualising the Test set results
2 from matplotlib.colors import ListedColormap
3 X_set, y_set = sc.inverse_transform(X_test), y_test
4 X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 10, stop = X_set[:, 0].max() + 10, step = 0.25),
                       np.arange(start = X_set[:, 1].min() - 1000, stop = X_set[:, 1].max() + 1000, step = 0.25))
6 plt.contourf(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel(), X2.ravel()]).T)).reshape(X1.shape),
               alpha = 0.75, cmap = ListedColormap(('red', 'green')))
8 plt.xlim(X1.min(), X1.max())
9 plt.ylim(X2.min(), X2.max())
10 for i, j in enumerate(np.unique(y_set)):
      plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)
12 plt.title('Naive Bayes (Test set)')
13 plt.xlabel('Age')
14 plt.ylabel('Estimated Salary')
15 plt.legend()
16 plt.show()
```

<ipython-input-10-aa7eb57ae484>:11: UserWarning: *c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)



*Decision Tree Classifier

```
1 # Importing the libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd
1 # Importing the dataset
2 dataset = pd.read_csv('Social_Network_Ads.csv')
3 X = dataset.iloc[:, :-1].values
4 y = dataset.iloc[:, -1].values
1 # Splitting the dataset into the Training set and Test set
2 from sklearn.model_selection import train_test_split
3 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)
4 print(X_train)
5 print(y_train)
6 print(X_test)
7 print(y_test)
          44 39000]
    [[
          32 120000]
          38 50000]
          32 135000]
          52 21000]
          53 104000]
          39
              42000]
              61000]
          38
              500001
          36
          36
              63000]
              25000]
          35
          35
              500001
          42
              73000]
          47
              49000]
          59
              29000]
              650001
          49
          45 131000]
          31
              89000]
          46
              820001
          47
              51000]
          26
              15000]
          60 102000]
          38 112000]
          40 107000]
             53000]
          35
              590001
          48
              41000]
          48 134000]
```

```
38 113000]
         29 1480001
         26 15000]
         60 42000]
         24 19000]
         42 149000]
          46
             96000]
         28 59000]
             960001
         39
         28
             89000]
         41 72000]
         45
             260001
         33
             690001
             82000]
         31
             74000]
         42 800001
         35 72000]
          33 149000]
          40 71000]
         51 146000]
         46
             79000]
         35 75000]
          38
             510001
          36
             75000]
         37 78000]
         38 610001
         60 108000]
          20 82000]
          57
             74000]
1 # Feature Scaling
2 from sklearn.preprocessing import StandardScaler
3 sc = StandardScaler()
4 X_train = sc.fit_transform(X_train)
5 X_test = sc.transform(X_test)
6 print(X_train)
7 print(X_test)
    [[ 0.58164944 -0.88670699]
     [-0.60673761 1.46173768]
     [-0.01254409 -0.5677824 ]
     [-0.60673761 1.89663484]
     [ 1.37390747 -1.40858358]
     [ 1.47293972 0.99784738]
     [ 0.08648817 -0.79972756]
     [-0.01254409 -0.24885782]
     [-0.21060859 -0.5677824 ]
     [-0.21060859 -0.19087153]
     [-0.30964085 -1.29261101]
     [-0.30964085 -0.5677824 ]
     [ 0.38358493  0.09905991]
     [ 0.8787462 -0.59677555]
     [ 2.06713324 -1.17663843]
     [ 1.07681071 -0.13288524]
     [ 0.68068169 1.78066227]
     [-0.70576986 0.56295021]
      0.77971394 0.35999821]
     [ 0.8787462 -0.53878926]
     [-1.20093113 -1.58254245]
     [ 2.1661655  0.93986109]
     [-0.01254409 1.22979253]
     [ 0.38358493 -0.48080297]
     [-0.30964085 -0.30684411]
     [ 0.97777845 -0.8287207 ]
     [ 0.97777845 1.8676417 ]
     [-0.01254409 1.25878567]
     [-0.90383437 2.27354572]
     [-1.20093113 -1.58254245]
     [ 2.1661655 -0.79972756]
     [-1.39899564 -1.46656987]
     [ 0.38358493  2.30253886]
     [ 0.77971394  0.76590222]
     [-1.00286662 -0.30684411]
     [ 0.08648817  0.76590222]
     [-1.00286662 0.56295021]
     [ 0.28455268  0.07006676]
      0.68068169 -1.26361786]
     [-0.50770535 -0.01691267]
     [-1.79512465 0.35999821]
     [-0.70576986 0.12805305]
     [ 0.38358493  0.30201192]
     [-0.30964085 0.07006676]
```

```
[-0.50770535 2.30253886]
     [ 0.18552042  0.04107362]
     [ 1.27487521 2.21555943]
     [ 0.77971394  0.27301877]
     [-0.30964085 0.1570462 ]
     [-0.01254409 -0.53878926]
     [-0.21060859 0.1570462]
     [-0.11157634 0.24402563]
     [-0.01254409 -0.24885782]
     [ 2.1661655   1.11381995]
     [-1.79512465 0.35999821]
     [ 1.86906873  0.12805305]
     [ 0.38358493 -0.13288524]
1 from sklearn.tree import DecisionTreeClassifier
2 classifier= DecisionTreeClassifier(criterion='entropy',random_state=0)
3 classifier.fit(X_train, y_train)
                        {\tt DecisionTreeClassifier}
    DecisionTreeClassifier(criterion='entropy', random_state=0)
1 # Predicting a new result
2 print(classifier.predict(sc.transform([[30,87000]])))
    [0]
1 # Predicting the Test set results
2 y_pred = classifier.predict(X_test)
3 print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [1 0]
     [0 0]
     [1 0]
     [1 0]
     [0 0]
     [1 1]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [1 1]
     [0 0]
     [0 1]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 1]
     [1 1]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [1 1]
```

4 print(cm)

[[62 6] [3 29]] 0.91

5 accuracy_score(y_test, y_pred)

```
[1 1]
[0 0]
[0 0]
[1 0]
[1 1]
[1 1]
[0 0]
[7 0]

1 # Making the Confusion Matrix
2 from sklearn.metrics import confusion_matrix, accuracy_score
3 cm = confusion_matrix(y_test, y_pred)
```

```
1 # Visualising the Training set results
 2 from matplotlib.colors import ListedColormap
 3 X_set, y_set = sc.inverse_transform(X_train), y_train
 4 \; X1, \; X2 = np.meshgrid(np.arange(start = X_set[:, \, \emptyset].min() \, - \, 10, \; stop = X_set[:, \, \, \emptyset].max() \, + \, 10, \; step = \, 0.25),
                         np.arange(start = X_set[:, 1].min() - 1000, stop = X_set[:, 1].max() + 1000, step = 0.25))
 6 plt.contourf(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel()], X2.ravel()]).T)).reshape(X1.shape),
                alpha = 0.75, cmap = ListedColormap(('red', 'green')))
8 plt.xlim(X1.min(), X1.max())
 9 plt.ylim(X2.min(), X2.max())
10 for i, j in enumerate(np.unique(y_set)):
11
       plt.scatter(X\_set[y\_set == j, 0], X\_set[y\_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)
12 plt.title('Decision Tree Classification (Training set)')
13 plt.xlabel('Age')
14 plt.ylabel('Estimated Salary')
15 plt.legend()
16 plt.show()
```

<ipython-input-10-0bdb4b7ac97b>:11: UserWarning: *c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)



```
1 # Visualising the Test set results
 2 from matplotlib.colors import ListedColormap
 3 X_set, y_set = sc.inverse_transform(X_test), y_test
 4 X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 10, stop = X_set[:, 0].max() + 10, step = 0.25),
                        np.arange(start = X\_set[:, 1].min() - 1000, stop = X\_set[:, 1].max() + 1000, stop = 0.25))
 6 plt.contourf(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel(), X2.ravel()]).T)).reshape(X1.shape),
                alpha = 0.75, cmap = ListedColormap(('red', 'green')))
 8 plt.xlim(X1.min(), X1.max())
 9 plt.ylim(X2.min(), X2.max())
10 for i, j in enumerate(np.unique(y_set)):
      plt.scatter(X\_set[y\_set == j, \ 0], \ X\_set[y\_set == j, \ 1], \ c = ListedColormap(('red', 'green'))(i), \ label = j)
12 plt.title('Decision Tree Classification (Test set)')
13 plt.xlabel('Age')
14 plt.ylabel('Estimated Salary')
15 plt.legend()
16 plt.show()
```

<ipython-input-9-0d0bde521908>:11: UserWarning: *c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided a
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)



* Random Forest Classifier *

```
1 # Importing the libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd
1 # Importing the dataset
2 dataset = pd.read_csv('Social_Network_Ads.csv')
3 X = dataset.iloc[:, :-1].values
4 y = dataset.iloc[:, -1].values
1 # Splitting the dataset into the Training set and Test set
2 from sklearn.model_selection import train_test_split
3 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)
4 print(X_train)
5 print(y_train)
6 print(X_test)
7 print(y_test)
          44 39000]
    [[
          32 120000]
          38 500001
          32 135000]
          52 21000]
          53 104000]
          39
             420001
          38
              61000]
          36
              50000]
              630001
          36
```

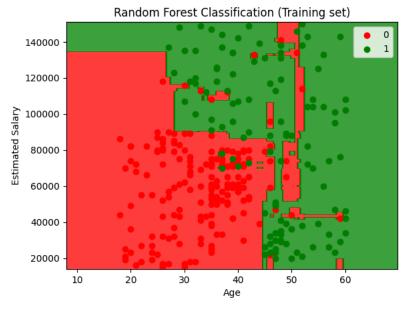
```
25000]
         35
         35 500001
         42 73000]
          47
             49000]
         59 29000]
         49 650001
         45 131000]
         31 89000]
             820001
         46
         47
             51000]
         26 15000]
         60 1020001
         38 112000]
          40 107000]
         42 53000]
         35 590001
         48 41000]
          48 134000]
         38 113000]
         29 148000]
         26
             15000]
         60 420001
         24 190001
          42 149000]
         46 96000]
         28
             590001
         39
             96000]
             89000]
         28
         41
             72000]
         45
             260001
         33
             69000]
         20
             82000]
             740001
         31
         42
             80000]
          35
             72000]
         33 1490001
         40 710001
         51 146000]
         46 79000]
             750001
         35
         38
             51000]
             75000]
         36
          37
             78000]
         38 610001
         60 108000]
         20
             82000]
    Γ
             740001
         57
         42 650001
1 # Feature Scaling
2 from sklearn.preprocessing import StandardScaler
3 sc = StandardScaler()
4 X_train = sc.fit_transform(X_train)
5 X_test = sc.transform(X_test)
6 print(X_train)
7 print(X_test)
   [[ 0.58164944 -0.88670699]
     [-0.60673761 1.46173768]
     [-0.01254409 -0.5677824 ]
    [-0.60673761 1.89663484]
     [ 1.37390747 -1.40858358]
    [ 1.47293972 0.99784738]
    [ 0.08648817 -0.79972756]
     [-0.01254409 -0.24885782]
     [-0.21060859 -0.5677824 ]
    [-0.21060859 -0.19087153]
     [-0.30964085 -1.29261101]
     [-0.30964085 -0.5677824 ]
     [ 0.38358493  0.09905991]
     [ 0.8787462 -0.59677555]
     [ 2.06713324 -1.17663843]
     [ 1.07681071 -0.13288524]
      0.68068169 1.78066227]
     [-0.70576986 0.56295021]
      0.77971394 0.35999821]
     [ 0.8787462 -0.53878926]
    [-1.20093113 -1.58254245]
     [ 2.1661655  0.93986109]
     [-0.01254409 1.22979253]
      0.18552042 1.08482681]
      0.38358493 -0.48080297]
     [-0.30964085 -0.30684411]
    [ 0.97777845 -0.8287207 ]
```

[0 0]

```
[ 0.97777845    1.8676417 ]
     [-0.01254409 1.25878567]
     [-0.90383437 2.27354572]
      -1.20093113 -1.58254245]
     [ 2.1661655 -0.79972756]
     [-1.39899564 -1.46656987]
     [ 0.38358493  2.30253886]
     [ 0.77971394  0.76590222]
     [-1.00286662 -0.30684411]
     [ 0.08648817  0.76590222]
     [-1.00286662 0.56295021]
     [ 0.28455268  0.07006676]
     [ 0.68068169 -1.26361786]
     [-0.50770535 -0.01691267]
     [-1.79512465 0.35999821]
     [-0.70576986 0.12805305]
     [ 0.38358493  0.30201192]
     [-0.30964085 0.07006676]
     [-0.50770535 2.30253886]
     [ 0.18552042  0.04107362]
       1.27487521 2.21555943]
     [ 0.77971394  0.27301877]
     [-0.30964085 0.1570462 ]
     [-0.01254409 -0.53878926]
     [-0.21060859 0.1570462]
     [-0.11157634 0.24402563]
     [-0.01254409 -0.24885782]
     [ 2.1661655    1.11381995]
     [-1.79512465 0.35999821]
     [ 1.86906873 0.12805305]
     [ 0.38358493 -0.13288524]
1 \# Training the Random Forest Classification model on the Training set
2 from sklearn.ensemble import RandomForestClassifier
3 classifier = RandomForestClassifier(n_estimators = 10, criterion = 'entropy', random_state = 0)
4 classifier.fit(X_train, y_train)
                                 {\tt RandomForestClassifier}
    RandomForestClassifier(criterion='entropy', n_estimators=10, random_state=0)
1 # Predicting a new result
2 print(classifier.predict(sc.transform([[30,87000]])))
    [0]
1 # Predicting the Test set results
2 y_pred = classifier.predict(X_test)
3 print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
    [[0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [1 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
     [1 0]
     [1 0]
     [0 0]
     [1 1]
     [0 0]
     [0 0]
     [1 1]
     [0 0]
     [1 1]
     [0 0]
     [0 1]
     [0 0]
     [0 0]
     [0 0]
     [0 0]
```

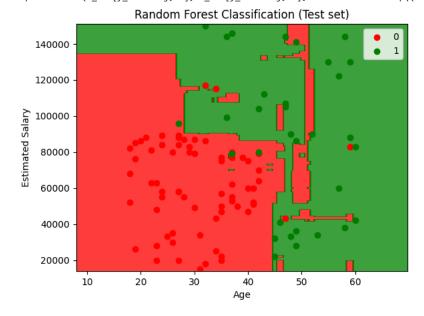
```
[0 1]
      [1 1]
      [0 0]
      [0 0]
      [0 0]
      [0 0]
      [0 0]
      [0 0]
      [1 1]
      [0 0]
      [0 0]
      [0 0]
      [0 0]
      [1 1]
      [0 0]
      [0 0]
      [1 1]
      [0 0]
      [1 1]
      [1 1]
      [0 0]
      [0 0]
      [1 0]
      [1 1]
      [1 1]
      [0 0]
      [0 0]
 1 # Making the Confusion Matrix
 2 from sklearn.metrics import confusion_matrix, accuracy_score
3 cm = confusion_matrix(y_test, y_pred)
 4 print(cm)
 5 accuracy_score(y_test, y_pred)
 6
     [[63 5]
     [ 4 28]]
     0.91
1 # Visualising the Training set results
 2 from matplotlib.colors import ListedColormap
 3 X_set, y_set = sc.inverse_transform(X_train), y_train
 4 \text{ X1, X2} = \text{np.meshgrid(np.arange(start = X\_set[:, 0].min() - 10, stop = X\_set[:, 0].max() + 10, step = 0.25),}
                        np.arange(start = X\_set[:, 1].min() - 1000, stop = X\_set[:, 1].max() + 1000, step = 0.25))
 6 plt.contourf(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel()], X2.ravel()]).T)).reshape(X1.shape),
                alpha = 0.75, cmap = ListedColormap(('red', 'green')))
 8 plt.xlim(X1.min(), X1.max())
 9 plt.ylim(X2.min(), X2.max())
10 for i, j in enumerate(np.unique(y_set)):
      plt.scatter(X\_set[y\_set == j, 0], X\_set[y\_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)
12 plt.title('Random Forest Classification (Training set)')
13 plt.xlabel('Age')
14 plt.ylabel('Estimated Salary')
15 plt.legend()
16 plt.show()
17
```

<ipython-input-19-d6b6ef8cb173>:11: UserWarning: *c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)



```
1 # Visualising the Test set results
 2 from matplotlib.colors import ListedColormap
 3 X_set, y_set = sc.inverse_transform(X_test), y_test
 4 X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 10, stop = X_set[:, 0].max() + 10, step = 0.25),
                        np.arange(start = X\_set[:, 1].min() - 1000, stop = X\_set[:, 1].max() + 1000, stop = 0.25))
 6 plt.contourf(X1, X2, classifier.predict(sc.transform(np.array([X1.ravel(), X2.ravel()]).T)).reshape(X1.shape),
                alpha = 0.75, cmap = ListedColormap(('red', 'green')))
 8 plt.xlim(X1.min(), X1.max())
 9 plt.ylim(X2.min(), X2.max())
10 for i, j in enumerate(np.unique(y_set)):
      plt.scatter(X\_set[y\_set == j, \ \emptyset], \ X\_set[y\_set == j, \ 1], \ c = ListedColormap(('red', 'green'))(i), \ label = j)
12 plt.title('Random Forest Classification (Test set)')
13 plt.xlabel('Age')
14 plt.ylabel('Estimated Salary')
15 plt.legend()
16 plt.show()
```

<ipython-input-20-4f1e0d3254dd>:11: UserWarning: *c* argument looks like a single numeric RGB or RGBA sequence, which should be avoided
plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'green'))(i), label = j)



Clustering K-Means*

```
1 # Importing the libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd
5

1 # Importing the dataset
2 dataset = pd.read_csv('Mall_Customers.csv')
3 X = dataset.iloc[:, [3, 4]].values
```

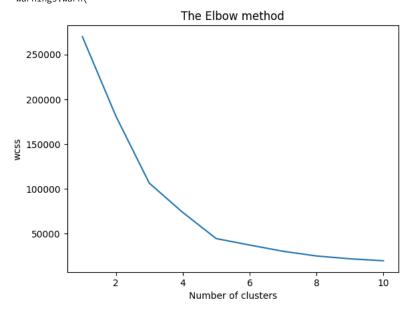
1 dataset

	CustomerID	Genre	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

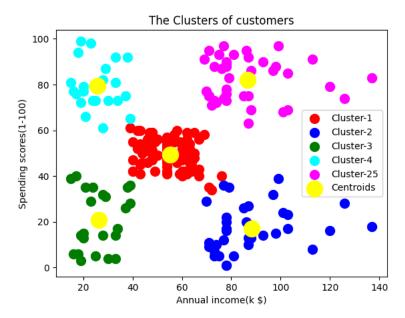
200 rows × 5 columns

```
1 #Using Elbow method to find optimal number of cluster
2
3 from sklearn.cluster import KMeans
4 wcss=[]
5 for i in range(1,11):
6    kmeans=KMeans(n_clusters = i,init='k-means++',random_state=42)
7    kmeans.fit(X)
8    wcss.append(kmeans.inertia_)
9 plt.plot(range(1,11),wcss)
10 plt.title('The Elbow method')
11 plt.xlabel('Number of clusters')
12 plt.ylabel('wcss')
13 plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10
 warnings.warn(
```



```
1 #Training K-means model on dataset
   2 kmeans=KMeans(n_clusters = 5,init='k-means++',random_state=42)
   3 y_kmeans=kmeans.fit_predict(X)
             /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10
                  warnings.warn(
   1 print(y_kmeans)
             1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4\; 1\; 4
                4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 ]
  1 #Visualize the clusters
   4 plt.scatter(X[y_kmeans==1,0], X[y_kmeans==1,1],s=100,c='blue',label='Cluster-2')
   5 plt.scatter(X[y_kmeans==2,0], X[y_kmeans==2,1],s=100,c='green',label='Cluster-3')
   \texttt{6 plt.scatter}(X[y\_kmeans=3,0], \ X[y\_kmeans=3,1],s=100,c='cyan',label='Cluster-4') \\
   7 plt.scatter(X[y_kmeans==4,0], X[y_kmeans==4,1], s=100, c='magenta', label='Cluster-25')
   8 plt.scatter(kmeans.cluster_centers_[:,0],kmeans.cluster_centers_[:,1],s=300,c='yellow',label='Centroids')
  9 plt.title('The Clusters of customers')
10 plt.xlabel('Annual income(k $)')
11 plt.ylabel('Spending scores(1-100)')
12 plt.legend()
13 plt.show()
```

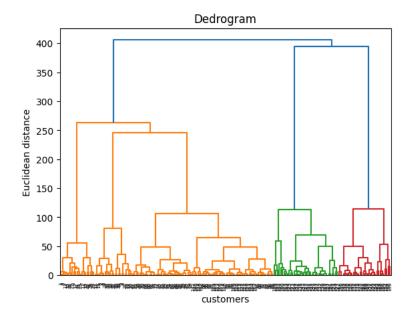


Hierachical Clustering

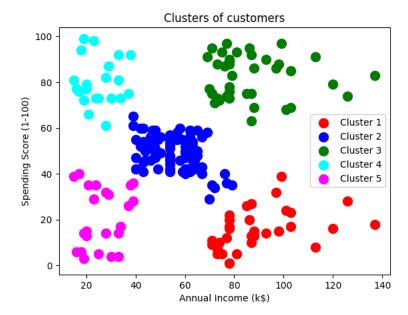
```
1 # Importing the libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd

1 # Importing the dataset
2 dataset = pd.read_csv('Mall_Customers.csv')
3 X = dataset.iloc[:, [3, 4]].values
4

1 #Using the dentrogram to find optimal number of cluster
2 import scipy.cluster.hierarchy as sch
3 dendrogram= sch.dendrogram(sch.linkage(X,method='ward'))
4 plt.title('Dedrogram')
5 plt.xlabel('customers')
6 plt.ylabel('Euclidean distance')
7 plt.show()
```



```
1 #Training the Hirerarchical Clustering model on the dataset
   2 from sklearn.cluster import AgglomerativeClustering
  3 hc=AgglomerativeClustering(n_clusters=5, affinity='euclidean',linkage='ward')
  4 y_hc=hc.fit_predict(X)
             /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_agglomerative.py:983: FutureWarning: Attribute `affinity` was deprecated in ver
                 warnings.warn(
  1 print(y_hc)
             0\; 2\; 0\; 2\; 0\; 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\; 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\; 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\; 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\; 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\; 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\; 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\; 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\; 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\; 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\; 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\; 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
               2020202020202021
  1 # Visualising the clusters
  2 plt.scatter(X[y_hc == 0, 0], X[y_hc == 0, 1], s = 100, c = 'red', label = 'Cluster 1')
  3 plt.scatter(X[y_hc == 1, 0], X[y_hc == 1, 1], s = 100, c = 'blue', label = 'Cluster 2')
  4 plt.scatter(X[y_hc == 2, 0], X[y_hc == 2, 1], s = 100, c = 'green', label = 'Cluster 3')
  5 plt.scatter(X[y_hc == 3, 0], X[y_hc == 3, 1], s = 100, c = 'cyan', label = 'Cluster 4')
  6 plt.scatter(X[y_hc == 4, 0], X[y_hc == 4, 1], s = 100, c = 'magenta', label = 'Cluster 5')
  7 plt.title('Clusters of customers')
  8 plt.xlabel('Annual Income (k$)')
  9 plt.ylabel('Spending Score (1-100)')
10 plt.legend()
11 plt.show()
```



Double-click (or enter) to edit

* Association Rule Leraning [People who bought also bought]*

```
Collecting apyori

Downloading apyori-1.1.2.tar.gz (8.6 kB)

Preparing metadata (setup.py) ... done

Building wheels for collected packages: apyori

Building wheel for apyori (setup.py) ... done

Created wheel for apyori: filename=apyori-1.1.2-py3-none-any.whl size=5955 sha256=9a9748efbc8b90c1ab24c2600d604558cf48e5b90bffb246925e

Stored in directory: /root/.cache/pip/wheels/c4/1a/79/20f55c470a50bb3702a8cb7c94d8ada15573538c7f4baebe2d

Successfully built apyori

Installing collected packages: apyori

Successfully installed apyori-1.1.2
```

```
1 # Importing the libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd
1 # Data Preprocessing
2 dataset = pd.read csv('Market Basket Optimisation.csv', header = None)
3 transactions = []
4 for i in range(0, 7501):
5 transactions.append([str(dataset.values[i,j]) for j in range(0, 20)])
1 # Training the Apriori model on the dataset
2 from apyori import apriori
3 rules = apriori(transactions = transactions, min_support = 0.003, min_confidence = 0.2, min_lift = 3, min_length = 2, max_length = 2)
1 results = list(rules)
2 results
      [RelationRecord(items=frozenset({'light cream', 'chicken'}), support=0.004532728969470737, ordered statistics=
      [OrderedStatistic(items_base=frozenset({'light cream'}), items_add=frozenset({'chicken'}), confidence=0.29059829059829057,
      lift=4.84395061728395)]),
       RelationRecord(items=frozenset({'mushroom cream sauce', 'escalope'}), support=0.005732568990801226, ordered_statistics=
      [OrderedStatistic(items base=frozenset({'mushroom cream sauce'}), items add=frozenset({'escalope'}), confidence=0.3006993006993007,
      lift=3.790832696715049)]),
       Relation Record (items=frozenset (\{ 'pasta', 'escalope' \}), \ support=0.005865884548726837, \ ordered\_statistics=1.005865884548726837, \ ordered\_statistics=1.005866884548726837, \ ordered\_statistics=1.005866884548726837, \ ordered\_statistics=1.005866884548726837, \ ordered\_statistics=1.005866884548726837, \ ordered\_statistics=1.005866884548726837, \ ordered\_statistics=1.0058668847, \ ordered\_statistics=1.0058668847, \ ordered\_statistics=1.0058668847, \ ordered\_statistics=1.005868847, \ ordered\_statistics=1.0058687,
      [OrderedStatistic(items_base=frozenset({'pasta'}), items_add=frozenset({'escalope'}), confidence=0.3728813559322034,
      lift=4.700811850163794)]),
       RelationRecord(items=frozenset({'fromage blanc', 'honey'}), support=0.003332888948140248, ordered_statistics=
      [OrderedStatistic(items_base=frozenset({'fromage blanc'}), items_add=frozenset({'honey'}), confidence=0.2450980392156863,
      lift=5.164270764485569)]).
       RelationRecord(items=frozenset({'ground beef', 'herb & pepper'}), support=0.015997866951073192, ordered_statistics=
      [OrderedStatistic(items_base=frozenset({'herb & pepper'}), items_add=frozenset({'ground beef'}), confidence=0.3234501347708895,
      lift=3.2919938411349285)]),
       RelationRecord(items=frozenset({'ground beef', 'tomato sauce'}), support=0.005332622317024397, ordered statistics=
      [OrderedStatistic(items_base=frozenset({'tomato sauce'}), items_add=frozenset({'ground beef'}), confidence=0.3773584905660377,
      lift=3.840659481324083)]),
       RelationRecord(items=frozenset({'olive oil', 'light cream'}), support=0.003199573390214638, ordered statistics=
      [OrderedStatistic(items_base=frozenset({'light cream'}), items_add=frozenset({'olive oil'}), confidence=0.20512820512820515,
      lift=3.1147098515519573)]),
       RelationRecord(items=frozenset({'olive oil', 'whole wheat pasta'}), support=0.007998933475536596, ordered_statistics=
      [OrderedStatistic(items_base=frozenset({'whole wheat pasta'}), items_add=frozenset({'olive oil'}), confidence=0.2714932126696833,
      lift=4.122410097642296)]),
       RelationRecord(items=frozenset({'shrimp', 'pasta'}), support=0.005065991201173177, ordered_statistics=
      [OrderedStatistic(items_base=frozenset({'pasta'}), items_add=frozenset({'shrimp'}), confidence=0.3220338983050847,
      lift=4.506672147735896)])]
1 ## Putting the results well organised into a Pandas DataFrame
2 def inspect(results):
        lhs
3
                            = [tuple(result[2][0][0])[0] for result in results]
4
                            = [tuple(result[2][0][1])[0] for result in results]
5
                          = [result[1] for result in results]
6
         confidences = [result[2][0][2] for result in results]
7
                            = [result[2][0][3] for result in results]
        return list(zip(lhs, rhs, supports, confidences, lifts))
8
9 resultsinDataFrame = pd.DataFrame(inspect(results), columns = ['Left Hand Side', 'Right Hand Side', 'Support', 'Confidence', 'Lift'])
1 ## Displaying the results non sorted
```

2 resultsinDataFrame

	Left Hand Side	Right Hand Side	Support	Confidence	Lift
0	light cream	chicken	0.004533	0.290598	4.843951
1	mushroom cream sauce	escalope	0.005733	0.300699	3.790833
2	pasta	escalope	0.005866	0.372881	4.700812
3	fromage blanc	honey	0.003333	0.245098	5.164271
4	herb & pepper	ground beef	0.015998	0.323450	3.291994
5	tomato sauce	ground beef	0.005333	0.377358	3.840659
6	light cream	olive oil	0.003200	0.205128	3.114710
7	whole wheat pasta	olive oil	0.007999	0.271493	4.122410
8	pasta	shrimp	0.005066	0.322034	4.506672

1 ## Displaying the results sorted by descending lifts
2 resultsinDataFrame.nlargest(n = 10, columns = 'Lift')

	Left Hand Side	Right Hand Side	Support	Confidence	Lift
3	fromage blanc	honey	0.003333	0.245098	5.164271
0	light cream	chicken	0.004533	0.290598	4.843951
2	pasta	escalope	0.005866	0.372881	4.700812
8	pasta	shrimp	0.005066	0.322034	4.506672
7	whole wheat pasta	olive oil	0.007999	0.271493	4.122410
5	tomato sauce	ground beef	0.005333	0.377358	3.840659
1	mushroom cream sauce	escalope	0.005733	0.300699	3.790833
4	herb & pepper	ground beef	0.015998	0.323450	3.291994
6	light cream	olive oil	0.003200	0.205128	3.114710

*Associate Rule Learning-- ECALT Tution *

```
1 # Importing the libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd
1 # Data Preprocessing
2 dataset = pd.read csv('Market Basket Optimisation.csv', header = None)
3 transactions = []
4 for i in range(0, 7501):
5 transactions.append([str(dataset.values[i,j]) for j in range(0, 20)])
1 pip install apyori
   Collecting apyori
     Downloading apyori-1.1.2.tar.gz (8.6 kB)
     Preparing metadata (setup.py) ... done
   Building wheels for collected packages: apyori
     Building wheel for apyori (setup.py) \dots done
     Created wheel for apyori: filename=apyori-1.1.2-py3-none-any.whl size=5955 sha256=6eb354319773b8de3c58e3feb3b2e0171cbc2055ee44f4d7cb62
     Stored in directory: /root/.cache/pip/wheels/c4/1a/79/20f55c470a50bb3702a8cb7c94d8ada15573538c7f4baebe2d
   Successfully built apyori
   Installing collected packages: apyori
   Successfully installed apyori-1.1.2
1 # Training the Eclat model on the dataset
2 from apvori import apriori
3 rules = apriori(transactions = transactions, min_support = 0.003, min_confidence = 0.2, min_lift = 3, min_length = 2, max_length = 2)
1 # Visualising the results
3 ## Displaying the first results coming directly from the output of the apriori function
4 results = list(rules)
5 results
   [RelationRecord(items=frozenset({'chicken', 'light cream'}), support=0.004532728969470737, ordered_statistics=
   [OrderedStatistic(items_base=frozenset({'light cream'}), items_add=frozenset({'chicken'}), confidence=0.29059829059829057,
   lift=4.84395061728395)]),
    [OrderedStatistic(items_base=frozenset({'mushroom cream sauce'}), items_add=frozenset({'escalope'}), confidence=0.3006993006993007,
   lift=3.790832696715049)]),
    RelationRecord(items=frozenset({'escalope', 'pasta'}), support=0.005865884548726837, ordered_statistics=
   [OrderedStatistic(items_base=frozenset({'pasta'}), items_add=frozenset({'escalope'}), confidence=0.3728813559322034,
   lift=4.700811850163794)]),
    RelationRecord(items=frozenset({'honey', 'fromage blanc'}), support=0.003332888948140248, ordered_statistics=
   [OrderedStatistic(items_base=frozenset({'fromage blanc'}), items_add=frozenset({'honey'}), confidence=0.2450980392156863,
   lift=5.164270764485569)]),
    [OrderedStatistic(items_base=frozenset({'herb & pepper'}), items_add=frozenset({'ground beef'}), confidence=0.3234501347708895,
   lift=3.2919938411349285)]),
    RelationRecord(items=frozenset({'tomato sauce', 'ground beef'}), support=0.005332622317024397, ordered_statistics=
   [OrderedStatistic(items_base=frozenset({'tomato sauce'}), items_add=frozenset({'ground beef'}), confidence=0.3773584905660377,
```

```
lift=3.840659481324083)]),
           RelationRecord(items=frozenset({'olive oil', 'light cream'}), support=0.003199573390214638, ordered statistics=
          [OrderedStatistic(items_base=frozenset({'light cream'}), items_add=frozenset({'olive oil'}), confidence=0.20512820512820515,
          lift=3.1147098515519573)]),
            RelationRecord(items=frozenset({'whole wheat pasta', 'olive oil'}), support=0.007998933475536596, ordered_statistics=
          [OrderedStatistic(items_base=frozenset({'whole wheat pasta'}), items_add=frozenset({'olive oil'}), confidence=0.2714932126696833,
          lift=4.122410097642296)]),
           Relation Record (items=frozenset (\{'shrimp', 'pasta'\}), support=0.005065991201173177, ordered\_statistics=0.005065991201173177, ordered\_statistics=0.0050679117, ordered\_statistic
          [OrderedStatistic(items_base=frozenset({'pasta'}), items_add=frozenset({'shrimp'}), confidence=0.3220338983050847,
          lift=4.506672147735896)])]
1 ## Putting the results well organised into a Pandas DataFrame
2 def inspect(results):
             1hs
3
                                             = [tuple(result[2][0][0])[0] for result in results]
4
                                             = [tuple(result[2][0][1])[0] for result in results]
5
                                          = [result[1] for result in results]
             return list(zip(lhs, rhs, supports))
6
7 resultsinDataFrame = pd.DataFrame(inspect(results), columns = ['Product 1', 'Product 2', 'Support'])
1 ## Displaying the results sorted by descending supports
2 resultsinDataFrame.nlargest(n = 10, columns = 'Support')
```

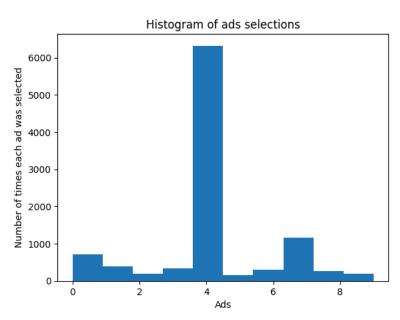
	Product 1	Product 2	Support
4	herb & pepper	ground beef	0.015998
7	whole wheat pasta	olive oil	0.007999
2	pasta	escalope	0.005866
1	mushroom cream sauce	escalope	0.005733
5	tomato sauce	ground beef	0.005333
8	pasta	shrimp	0.005066
0	light cream	chicken	0.004533
3	fromage blanc	honey	0.003333
6	light cream	olive oil	0.003200

Upper Confidence Bound (UCB)

```
1 # Importing the libraries
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd

1 # Importing the dataset
2 dataset = pd.read_csv('Ads_CTR_Optimisation.csv')
```

```
1 # Implementing UCB
 2 import math
3 N = 10000
4 d = 10
 5 ads_selected = []
 6 numbers_of_selections = [0] * d
 7 \text{ sums\_of\_rewards} = [0] * d
 8 total_reward = 0
 9 for n in range(0, N):
10
      ad = 0
      max\_upper\_bound = 0
11
12
       for i in range(0, d):
13
           if (numbers_of_selections[i] > 0):
               average reward = sums of rewards[i] / numbers of selections[i]
14
               delta_i = math.sqrt(3/2 * math.log(n + 1) / numbers_of_selections[i])
15
16
               upper_bound = average_reward + delta_i
17
           else:
18
               upper_bound = 1e400
19
           if upper_bound > max_upper_bound:
20
               max\_upper\_bound = upper\_bound
21
               ad = i
22
       ads_selected.append(ad)
      numbers_of_selections[ad] = numbers_of_selections[ad] + 1
23
24
      reward = dataset.values[n, ad]
25
       sums_of_rewards[ad] = sums_of_rewards[ad] + reward
26
       total_reward = total_reward + reward
 1 # Visualising the results
 2 plt.hist(ads_selected)
3 plt.title('Histogram of ads selections')
4 plt.xlabel('Ads')
 5 plt.ylabel('Number of times each ad was selected')
 6 plt.show()
```



NLP Natural language processing

```
1 #Bag of word
2 # Importing the libraries
3 import numpy as np
4 import matplotlib.pyplot as plt
5 import pandas as pd

1 #Importing the dataset : note quoting 3 is used to remove "" from comment
2 dataset = pd.read_csv('Restaurant_Reviews.tsv', delimiter = '\t',quoting=3)
```

```
1 #Cleaning the text
 2 import re
3 import nltk
4 nltk.download('stopwords')
5 from nltk.corpus import stopwords
6 from nltk.stem.porter import PorterStemmer
 7 corpus = []
8 for i in range(0, 1000):
9 review = re.sub('[^a-zA-Z]', ' ', dataset['Review'][i])
10 review = review.lower()
11 review = review.split()
12
    ps = PorterStemmer()
13 all_stopwords = stopwords.words('english')
14 all stopwords.remove('not')
15 review = [ps.stem(word) for word in review if not word in set(all_stopwords)]
16 review = ' '.join(review)
17 corpus.append(review)
18 print(corpus)
     [nltk_data] Downloading package stopwords to /root/nltk_data...
     [nltk_data] Unzipping corpora/stopwords.zip.
     ['wow love place', 'crust not good', 'not tasti textur nasti', 'stop late may bank holiday rick steve recommend love', 'select menu grea
1 #Creating a Bag words
 2 from sklearn.feature_extraction.text import CountVectorizer
 3 cv = CountVectorizer(max_features = 1500)
4 X = cv.fit\_transform(corpus).toarray()
 5 y = dataset.iloc[:, -1].values
 1 len(X[0])
     1500
 1 # Splitting the dataset into the Training set and Test set
 2 from sklearn.model_selection import train_test_split
 3 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 0)
 1 # Training the Naive Bayes model on the Training set
 2 from sklearn.naive_bayes import GaussianNB
 3 classifier = GaussianNB()
 4 classifier.fit(X_train, y_train)
     ▼ GaussianNB
     GaussianNB()
 1 \# Predicting the Test set results
 2 y pred = classifier.predict(X test)
 3 print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
     [[1 0]
      [1 0]
      [1 0]
      [0 0]
      [0 0]
      [1 0]
      [1 1]
      [1 0]
      [1 0]
      [1 1]
      [1 1]
      [1 1]
      [1 0]
      [1 1]
      [1 1]
      [1 1]
      [0 0]
      [0 0]
      [0 0]
      [1 1]
      [0 0]
      [0 1]
      [1 1]
      [1 0]
      [1 0]
```

```
11/04/2024. 23:48
```

```
[0 1]
     [1 1]
     [1 1]
     [1 1]
     [0 0]
     [1 1]
     [1 1]
     [1 1]
     [1 1]
     [1 1]
     [0 0]
     [1 0]
     [0 0]
     [1 0]
     [1 1]
     [1 1]
     [1 0]
     [1 1]
     [0 0]
     [0 0]
     [0 0]
     [1 0]
     [1 0]
     [0 0]
     [0 0]
     [1 1]
     [1 1]
     [1 1]
     [1 1]
     [1 0]
     [0 0]
     [1 1]
1 # Making the Confusion Matrix
2 from sklearn.metrics import confusion_matrix, accuracy_score
3 cm = confusion_matrix(y_test, y_pred)
4 print(cm)
5 accuracy_score(y_test, y_pred)
    [[55 42]
```

Predicting if a single review is positive or negative

[12 91]] 0.73

```
1 new_review = 'I love this restaurant so much'
2 new_review = re.sub('[^a-zA-Z]', ' ', new_review)
3 new_review = new_review.lower()
4 new_review = new_review.split()
5 ps = PorterStemmer()
6 all_stopwords = stopwords.words('english')
7 all_stopwords.remove('not')
8 new_review = [ps.stem(word) for word in new_review if not word in set(all_stopwords)]
9 new_review = ' '.join(new_review)
10 new_corpus = [new_review]
11 new_X_test = cv.transform(new_corpus).toarray()
12 new_y_pred = classifier.predict(new_X_test)
13 print(new_y_pred)
    [1]
1 new review = 'I hate this restaurant so much'
2 new_review = re.sub('[^a-zA-Z]', ' ', new_review)
3 new_review = new_review.lower()
4 new_review = new_review.split()
5 ps = PorterStemmer()
6 all_stopwords = stopwords.words('english')
7 all_stopwords.remove('not')
8 new_review = [ps.stem(word) for word in new_review if not word in set(all_stopwords)]
9 new_review = ' '.join(new_review)
10 new_corpus = [new_review]
11 new_X_test = cv.transform(new_corpus).toarray()
12 new_y_pred = classifier.predict(new_X_test)
13 print(new_y_pred)
    [0]
```

Importing the Libraries

```
1 # Importing the libraries
 2 import numpy as np
 3 import matplotlib.pyplot as plt
 4 import pandas as pd
 1 #Importing dataset - quoting is used to remove " from the text
 2 dataset=pd.read_csv('/content/Restaurant_Reviews.tsv',sep='\t', quoting=3)
 1 dataset.head()
                                            Review Liked
     0
                              Wow... Loved this place.
      1
                                    Crust is not good.
                                                        0
     2
                 Not tasty and the texture was just nasty.
                                                        0
     3
          Stopped by during the late May bank holiday of...
                                                        1
      4 The selection on the menu was great and so wer...
1 # Cleaning the texts
 2 import re
 3 import nltk
4 nltk.download('stopwords')
 5 from nltk.corpus import stopwords
6 from nltk.stem.porter import PorterStemmer
 7 corpus = []
8 for i in range(0, 1000):
9 review = re.sub('[^a-zA-Z]', ' ', dataset['Review'][i])
10
    review = review.lower()
11 review = review.split()
ps = PorterStemmer()
13 all_stopwords = stopwords.words('english')
14 all_stopwords.remove('not')
15 review = [ps.stem(word) for word in review if not word in set(all_stopwords)]
16 review = ' '.join(review)
17 corpus.append(review)
18 print(corpus)
     [nltk_data] Downloading package stopwords to /root/nltk_data...
                  Package stopwords is already up-to-date!
     ['wow love place', 'crust not good', 'not tasti textur nasti', 'stop late may bank holiday rick steve recommend love', 'select menu grea
 1 print(corpus)
     ['wow love place', 'crust not good', 'not tasti textur nasti', 'stop late may bank holiday rick steve recommend love', 'select menu grea
    4
 1 # Creating the Bag of Words model
 2 from sklearn.feature_extraction.text import CountVectorizer
 3 cv = CountVectorizer(max_features = 1500)
 4 X = cv.fit_transform(corpus).toarray()
 5 y = dataset.iloc[:, -1].values
 1 len(X[0])
     1500
1 # Splitting the dataset into the Training set and Test set
 2 from sklearn.model_selection import train_test_split
 3 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 0)
1 # Training the Naive Bayes model on the Training set
 2 from sklearn.naive_bayes import GaussianNB
 3 classifier = GaussianNB()
 4 classifier.fit(X_train, y_train)
```

[0 0] [0 0] [0 0]

```
▼ GaussianNB
     GaussianNB()
1 # Predicting the Test set results
2 y_pred = classifier.predict(X_test)
 \texttt{3 print(np.concatenate((y\_pred.reshape(len(y\_pred),1), y\_test.reshape(len(y\_test),1)),1))} \\
    [[1 0]
      [1 0]
     [1 0]
[1 0]
      [0 0]
      [1 0]
      [1 1]
[1 0]
      [1 0]
      [1 1]
      [1 1]
      [1 1]
      [1 0]
      [1 1]
      [1 1]
      [1 1]
```