Practical No 1 : Simple Linear Regression

Importing the libraries

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

Importing the dataset

In [2]:
```
dataset = pd.read_csv('Salary_Data.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
```

Splitting the dataset into the Training set and Test set

In [3]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 1/3, random_state = 0)
```

Training the Simple Linear Regression model on the Training set

In [4]:
```
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[4]:
```
LinearRegression()
```

Predicting the Test set results

In [5]:
```
y_pred = regressor.predict(X_test)
```

Visualising the Training set results

In [6]:
```
plt.scatter(X_train, y_train, color = 'red')
plt.plot(X_train, regressor.predict(X_train), color = 'blue')
plt.title('Salary vs Experience (Training set)')
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
plt.show()
```

Visualising the Test set results

In [9]:
```
plt.scatter(X_test, y_test, color = 'red')
plt.plot(X_train, regressor.predict(X_train), color = 'blue')
plt.title('Salary vs Experience (Test set)')
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
```

```python
plt.show()
```

Practical No - 2 : Multiple Linear Regression

Importing the libraries

In [1]:
```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

Importing the dataset

In [2]:
```python
dataset = pd.read_csv('50_Startups.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
```

In [3]:
```python
print(X)
```

```
[[165349.2 136897.8 471784.1 'New York']
 [162597.7 151377.59 443898.53 'California']
 [153441.51 101145.55 407934.54 'Florida']
 [144372.41 118671.85 383199.62 'New York']
 [142107.34 91391.77 366168.42 'Florida']
 [131876.9 99814.71 362861.36 'New York']
 [134615.46 147198.87 127716.82 'California']
 [130298.13 145530.06 323876.68 'Florida']
 [120542.52 148718.95 311613.29 'New York']
 [123334.88 108679.17 304981.62 'California']
 [101913.08 110594.11 229160.95 'Florida']
 [100671.96 91790.61 249744.55 'California']
 [93863.75 127320.38 249839.44 'Florida']
 [91992.39 135495.07 252664.93 'California']
 [119943.24 156547.42 256512.92 'Florida']
 [114523.61 122616.84 261776.23 'New York']
 [78013.11 121597.55 264346.06 'California']
 [94657.16 145077.58 282574.31 'New York']
 [91749.16 114175.79 294919.57 'Florida']
 [86419.7 153514.11 0.0 'New York']
 [76253.86 113867.3 298664.47 'California']
 [78389.47 153773.43 299737.29 'New York']
 [73994.56 122782.75 303319.26 'Florida']
 [67532.53 105751.03 304768.73 'Florida']
 [77044.01 99281.34 140574.81 'New York']
 [64664.71 139553.16 137962.62 'California']
 [75328.87 144135.98 134050.07 'Florida']
 [72107.6 127864.55 353183.81 'New York']
 [66051.52 182645.56 118148.2 'Florida']
 [65605.48 153032.06 107138.38 'New York']
 [61994.48 115641.28 91131.24 'Florida']
 [61136.38 152701.92 88218.23 'New York']
 [63408.86 129219.61 46085.25 'California']
 [55493.95 103057.49 214634.81 'Florida']
 [46426.07 157693.92 210797.67 'California']
 [46014.02 85047.44 205517.64 'New York']
 [28663.76 127056.21 201126.82 'Florida']
 [44069.95 51283.14 197029.42 'California']
 [20229.59 65947.93 185265.1 'New York']
 [38558.51 82982.09 174999.3 'California']
 [28754.33 118546.05 172795.67 'California']
 [27892.92 84710.77 164470.71 'Florida']
 [23640.93 96189.63 148001.11 'California']
 [15505.73 127382.3 35534.17 'New York']
 [22177.74 154806.14 28334.72 'California']
 [1000.23 124153.04 1903.93 'New York']
 [1315.46 115816.21 297114.46 'Florida']
 [0.0 135426.92 0.0 'California']
 [542.05 51743.15 0.0 'New York']
 [0.0 116983.8 45173.06 'California']]
```

Encoding categorical data

In [4]:
```python
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [3])], remainder='passthrough')
X = np.array(ct.fit_transform(X))
```

In [5]:
```python
print(X)
```

```
[[0.0 0.0 1.0 165349.2 136897.8 471784.1]
 [1.0 0.0 0.0 162597.7 151377.59 443898.53]
 [0.0 1.0 0.0 153441.51 101145.55 407934.54]
 [0.0 0.0 1.0 144372.41 118671.85 383199.62]
 [0.0 1.0 0.0 142107.34 91391.77 366168.42]
 [0.0 0.0 1.0 131876.9 99814.71 362861.36]
 [1.0 0.0 0.0 134615.46 147198.87 127716.82]
 [0.0 1.0 0.0 130298.13 145530.06 323876.68]
 [0.0 0.0 1.0 120542.52 148718.95 311613.29]
 [1.0 0.0 0.0 123334.88 108679.17 304981.62]
 [0.0 1.0 0.0 101913.08 110594.11 229160.95]
 [1.0 0.0 0.0 100671.96 91790.61 249744.55]
 [0.0 1.0 0.0 93863.75 127320.38 249839.44]
 [1.0 0.0 0.0 91992.39 135495.07 252664.93]
 [0.0 1.0 0.0 119943.24 156547.42 256512.92]
 [0.0 0.0 1.0 114523.61 122616.84 261776.23]
 [1.0 0.0 0.0 78013.11 121597.55 264346.06]
 [0.0 0.0 1.0 94657.16 145077.58 282574.31]
 [0.0 1.0 0.0 91749.16 114175.79 294919.57]
 [0.0 0.0 1.0 86419.7 153514.11 0.0]
 [1.0 0.0 0.0 76253.86 113867.3 298664.47]
 [0.0 0.0 1.0 78389.47 153773.43 299737.29]
 [0.0 1.0 0.0 73994.56 122782.75 303319.26]
 [0.0 1.0 0.0 67532.53 105751.03 304768.73]
 [0.0 0.0 1.0 77044.01 99281.34 140574.81]
 [1.0 0.0 0.0 64664.71 139553.16 137962.62]
 [0.0 1.0 0.0 75328.87 144135.98 134050.07]
 [0.0 0.0 1.0 72107.6 127864.55 353183.81]
 [0.0 1.0 0.0 66051.52 182645.56 118148.2]
 [0.0 0.0 1.0 65605.48 153032.06 107138.38]
 [0.0 1.0 0.0 61994.48 115641.28 91131.24]
 [0.0 0.0 1.0 61136.38 152701.92 88218.23]
 [1.0 0.0 0.0 63408.86 129219.61 46085.25]
 [0.0 1.0 0.0 55493.95 103057.49 214634.81]
 [1.0 0.0 0.0 46426.07 157693.92 210797.67]
 [0.0 0.0 1.0 46014.02 85047.44 205517.64]
 [0.0 1.0 0.0 28663.76 127056.21 201126.82]
 [1.0 0.0 0.0 44069.95 51283.14 197029.42]
 [0.0 0.0 1.0 20229.59 65947.93 185265.1]
 [1.0 0.0 0.0 38558.51 82982.09 174999.3]
 [1.0 0.0 0.0 28754.33 118546.05 172795.67]
 [0.0 1.0 0.0 27892.92 84710.77 164470.71]
 [1.0 0.0 0.0 23640.93 96189.63 148001.11]
 [0.0 0.0 1.0 15505.73 127382.3 35534.17]
 [1.0 0.0 0.0 22177.74 154806.14 28334.72]
 [0.0 0.0 1.0 1000.23 124153.04 1903.93]
 [0.0 1.0 0.0 1315.46 115816.21 297114.46]
 [1.0 0.0 0.0 0.0 135426.92 0.0]
 [0.0 0.0 1.0 542.05 51743.15 0.0]
 [1.0 0.0 0.0 0.0 116983.8 45173.06]]
```

Splitting the dataset into the Training set and Test set

In [6]:
```python
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
```

Training the Multiple Linear Regression model on the Training set

In [7]:
```python
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

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

Predicting the Test set results

In [8]:
```python
y_pred = regressor.predict(X_test)
np.set_printoptions(precision=2)
print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
```

```
[[103015.2  103282.38]
```

```
[132582.28 144259.4 ]
[132447.74 146121.95]
[ 71976.1   77798.83]
[178537.48 191050.39]
[116161.24 105008.31]
[ 67851.69  81229.06]
[ 98791.73  97483.56]
[113969.44 110352.25]
[167921.07 166187.94]]
```

In [ ]:

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js

Practical No - 3 : Support Vector Machine (SVM)

Importing the libraries

In [15]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

Importing the dataset

In [16]:
```
dataset = pd.read_csv('Social_Network_Ads.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
```

Splitting the dataset into the Training set and Test set

In [17]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)
```

In [18]:
```
print(X_train)
```

```
[[    44  39000]
 [    32 120000]
 [    38  50000]
 [    32 135000]
 [    52  21000]
 [    53 104000]
 [    39  42000]
 [    38  61000]
 [    36  50000]
 [    36  63000]
 [    35  25000]
 [    35  50000]
 [    42  73000]
 [    47  49000]
 [    59  29000]
 [    49  65000]
 [    45 131000]
 [    31  89000]
 [    46  82000]
 [    47  51000]
 [    26  15000]
 [    60 102000]
 [    38 112000]
 [    40 107000]
 [    42  53000]
 [    35  59000]
 [    48  41000]
 [    48 134000]
 [    38 113000]
 [    29 148000]
 [    26  15000]
 [    60  42000]
 [    24  19000]
 [    42 149000]
 [    46  96000]
 [    28  59000]
 [    39  96000]
 [    28  89000]
 [    41  72000]
 [    45  26000]
 [    33  69000]
 [    20  82000]
 [    31  74000]
 [    42  80000]
 [    35  72000]
 [    33 149000]
 [    40  71000]
 [    51 146000]
 [    46  79000]
 [    35  75000]
 [    38  51000]
 [    36  75000]
 [    37  78000]
 [    38  61000]
```

```
[    60 108000]
[    20  82000]
[    57  74000]
[    42  65000]
[    26  80000]
[    46 117000]
[    35  61000]
[    21  68000]
[    28  44000]
[    41  87000]
[    37  33000]
[    27  90000]
[    39  42000]
[    28 123000]
[    31 118000]
[    25  87000]
[    35  71000]
[    37  70000]
[    35  39000]
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[    31  18000]
[    31  71000]
[    43 129000]
[    59  76000]
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[    36 118000]
[    42  90000]
[    47  30000]
[    26  43000]
[    40  78000]
[    46  59000]
[    59  42000]
[    46  74000]
[    35  91000]
[    28  59000]
[    40  57000]
[    59 143000]
[    57  26000]
[    52  38000]
[    47 113000]
[    53 143000]
[    35  27000]
[    58 101000]
[    45  45000]
[    23  82000]
[    46  23000]
[    42  65000]
[    28  84000]
[    38  59000]
[    26  84000]
[    29  28000]
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[    38  65000]
[    27  17000]
[    46  28000]
[    48 141000]
[    26  17000]
[    35  97000]
[    39  59000]
[    24  27000]
[    32  18000]
[    46  88000]
[    35  58000]
[    56  60000]
[    47  34000]
[    40  72000]
[    32 100000]
[    19  21000]
```

```
[    25  90000]
[    35  88000]
[    28  32000]
[    50  20000]
[    40  59000]
[    50  44000]
[    35  72000]
[    40 142000]
[    46  32000]
[    39  71000]
[    20  74000]
[    29  75000]
[    31  76000]
[    47  25000]
[    40  61000]
[    34 112000]
[    38  80000]
[    42  75000]
[    47  47000]
[    39  75000]
[    19  25000]
[    37  80000]
[    36  60000]
[    41  52000]
[    36 125000]
[    48  29000]
[    36 126000]
[    51 134000]
[    27  57000]
[    38  71000]
[    39  61000]
[    22  27000]
[    33  60000]
[    48  74000]
[    58  23000]
[    53  72000]
[    32 117000]
[    54  70000]
[    30  80000]
[    58  95000]
[    26  52000]
[    45  79000]
[    24  55000]
[    40  75000]
[    33  28000]
[    44 139000]
[    22  18000]
[    33  51000]
[    43 133000]
[    24  32000]
[    46  22000]
[    35  55000]
[    54 104000]
[    48 119000]
[    35  53000]
[    37 144000]
[    23  66000]
[    37 137000]
[    31  58000]
[    33  41000]
[    45  22000]
[    30  15000]
[    19  19000]
[    49  74000]
[    39 122000]
[    35  73000]
[    39  71000]
[    24  23000]
[    41  72000]
[    29  83000]
[    54  26000]
[    35  44000]
[    37  75000]
[    29  47000]
[    31  68000]
[    42  54000]
[    30 135000]
[    52 114000]
[    50  36000]
[    56 133000]
[    29  61000]
[    30  89000]
[    26  16000]
```

```
 [    33  31000]
 [    41  72000]
 [    36  33000]
 [    55 125000]
 [    48 131000]
 [    41  71000]
 [    30  62000]
 [    37  72000]
 [    41  63000]
 [    58  47000]
 [    30 116000]
 [    20  49000]
 [    37  74000]
 [    41  59000]
 [    49  89000]
 [    28  79000]
 [    53  82000]
 [    40  57000]
 [    60  34000]
 [    35 108000]
 [    21  72000]
 [    38  71000]
 [    39 106000]
 [    37  57000]
 [    26  72000]
 [    35  23000]
 [    54 108000]
 [    30  17000]
 [    39 134000]
 [    29  43000]
 [    33  43000]
 [    35  38000]
 [    41  45000]
 [    41  72000]
 [    39 134000]
 [    27 137000]
 [    21  16000]
 [    26  32000]
 [    31  66000]
 [    39  73000]
 [    41  79000]
 [    47  50000]
 [    41  30000]
 [    37  93000]
 [    60  46000]
 [    25  22000]
 [    28  37000]
 [    38  55000]
 [    36  54000]
 [    20  36000]
 [    56 104000]
 [    40  57000]
 [    42 108000]
 [    20  23000]
 [    40  65000]
 [    47  20000]
 [    18  86000]
 [    35  79000]
 [    57  33000]
 [    34  72000]
 [    49  39000]
 [    27  31000]
 [    19  70000]
 [    39  79000]
 [    26  81000]
 [    25  80000]
 [    28  85000]
 [    55  39000]
 [    50  88000]
 [    49  88000]
 [    52 150000]
 [    35  65000]
 [    42  54000]
 [    34  43000]
 [    37  52000]
 [    48  30000]
 [    29  43000]
 [    36  52000]
 [    27  54000]
 [    26 118000]]
```

In [10]:

```
print(y_train)
```

In [19]:
```
print(y_train)
```

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

In [20]:
```
print(X_test)
```

```
[[    30  87000]
 [    38  50000]
 [    35  75000]
 [    30  79000]
 [    35  50000]
 [    27  20000]
 [    31  15000]
 [    36 144000]
 [    18  68000]
 [    47  43000]
 [    30  49000]
 [    28  55000]
 [    37  55000]
 [    39  77000]
 [    20  86000]
 [    32 117000]
 [    37  77000]
 [    19  85000]
 [    55 130000]
 [    35  22000]
 [    35  47000]
 [    47 144000]
 [    41  51000]
 [    47 105000]
 [    23  28000]
 [    49 141000]
 [    28  87000]
 [    29  80000]
 [    37  62000]
 [    32  86000]
 [    21  88000]
 [    37  79000]
 [    57  60000]
 [    37  53000]
 [    24  58000]
 [    18  52000]
 [    22  81000]
 [    34  43000]
 [    31  34000]
 [    49  36000]
 [    27  88000]
 [    41  52000]
 [    27  84000]
 [    35  20000]
 [    43 112000]
 [    27  58000]
 [    37  80000]
 [    52  90000]
 [    26  30000]
 [    49  86000]
 [    57 122000]
 [    34  25000]
 [    35  57000]
 [    34 115000]
 [    59  88000]
 [    45  32000]
 [    29  83000]
 [    26  80000]
 [    49  28000]
 [    23  20000]
 [    32  18000]
 [    60  42000]
 [    19  76000]
 [    36  99000]
 [    19  26000]
 [    60  83000]
 [    24  89000]
 [    27  58000]
```

```
 [    40  47000]
 [    42  70000]
 [    32 150000]
 [    35  77000]
 [    22  63000]
 [    45  22000]
 [    27  89000]
 [    18  82000]
 [    42  79000]
 [    40  60000]
 [    53  34000]
 [    47 107000]
 [    58 144000]
 [    59  83000]
 [    24  55000]
 [    26  35000]
 [    58  38000]
 [    42  80000]
 [    40  75000]
 [    59 130000]
 [    46  41000]
 [    41  60000]
 [    42  64000]
 [    37 146000]
 [    23  48000]
 [    25  33000]
 [    24  84000]
 [    27  96000]
 [    23  63000]
 [    48  33000]
 [    48  90000]
 [    42 104000]]
```

In [21]:
```
print(y_test)
```

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

Feature Scaling

In [22]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [23]:
```
print(X_train)
```

```
[[ 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]
[-1.20093113  0.30201192]
[ 0.77971394  1.37475825]
[-0.30964085 -0.24885782]
[-1.6960924  -0.04590581]
[-1.00286662 -0.74174127]
[ 0.28455268  0.50496393]
[-0.11157634 -1.06066585]
[-1.10189888  0.59194336]
[ 0.08648817 -0.79972756]
[-1.00286662  1.54871711]
[-0.70576986  1.40375139]
[-1.29996338  0.50496393]
[-0.30964085  0.04107362]
[-0.11157634  0.01208048]
[-0.30964085 -0.88670699]
[ 0.8787462  -1.3505973 ]
[-0.30964085  2.24455257]
[ 0.97777845  1.98361427]
[-1.20093113  0.47597078]
[-1.29996338  0.27301877]
[ 1.37390747  1.98361427]
[ 1.27487521 -1.3505973 ]
[-0.30964085 -0.27785096]
[-0.50770535  1.25878567]
[-0.80480212  1.08482681]
[ 0.97777845 -1.06066585]
[ 0.28455268  0.30201192]
[ 0.97777845  0.76590222]
[-0.70576986 -1.49556302]
[-0.70576986  0.04107362]
[ 0.48261718  1.72267598]
[ 2.06713324  0.18603934]
[-1.99318916 -0.74174127]
[-0.21060859  1.40375139]
[ 0.38358493  0.59194336]
[ 0.8787462  -1.14764529]
[-1.20093113 -0.77073441]
[ 0.18552042  0.24402563]
[ 0.77971394 -0.30684411]
[ 2.06713324 -0.79972756]
[ 0.77971394  0.12805305]
[-0.30964085  0.6209365 ]
[-1.00286662 -0.30684411]
[ 0.18552042 -0.3648304 ]
[ 2.06713324  2.12857999]
[ 1.86906873 -1.26361786]
[ 1.37390747 -0.91570013]
[ 0.8787462   1.25878567]
[ 1.47293972  2.12857999]
[-0.30964085 -1.23462472]
[ 1.96810099  0.91086794]
[ 0.68068169 -0.71274813]
[-1.49802789  0.35999821]
[ 0.77971394 -1.3505973 ]
[ 0.38358493 -0.13288524]
```

```
[-1.00286662  0.41798449]
[-0.01254409 -0.30684411]
[-1.20093113  0.41798449]
[-0.90383437 -1.20563157]
[-0.11157634  0.04107362]
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[ 0.97777845 -1.00267957]
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[-0.01254409 -0.13288524]
[-1.10189888 -1.52455616]
[ 0.77971394 -1.20563157]
[ 0.97777845  2.07059371]
[-1.20093113 -1.52455616]
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[ 0.08648817 -0.30684411]
[-1.39899564 -1.23462472]
[-0.60673761 -1.49556302]
[ 0.77971394  0.53395707]
[-0.30964085 -0.33583725]
[ 1.77003648 -0.27785096]
[ 0.8787462  -1.03167271]
[ 0.18552042  0.07006676]
[-0.60673761  0.8818748 ]
[-1.89415691 -1.40858358]
[-1.29996338  0.59194336]
[-0.30964085  0.53395707]
[-1.00286662 -1.089659  ]
[ 1.17584296 -1.43757673]
[ 0.18552042 -0.30684411]
[ 1.17584296 -0.74174127]
[-0.30964085  0.07006676]
[ 0.18552042  2.09958685]
[ 0.77971394 -1.089659  ]
[ 0.08648817  0.04107362]
[-1.79512465  0.12805305]
[-0.90383437  0.1570462 ]
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[ 0.8787462  -1.29261101]
[ 0.18552042 -0.24885782]
[-0.4086731   1.22979253]
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[ 0.8787462  -0.65476184]
[ 0.08648817  0.1570462 ]
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[-0.11157634  0.30201192]
[-0.21060859 -0.27785096]
[ 0.28455268 -0.50979612]
[-0.21060859  1.6067034 ]
[ 0.97777845 -1.17663843]
[-0.21060859  1.63569655]
[ 1.27487521  1.8676417 ]
[-1.10189888 -0.3648304 ]
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[ 0.08648817 -0.24885782]
[-1.59706014 -1.23462472]
[-0.50770535 -0.27785096]
[ 0.97777845  0.12805305]
[ 1.96810099 -1.3505973 ]
[ 1.47293972  0.07006676]
[-0.60673761  1.37475825]
[ 1.57197197  0.01208048]
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[ 1.96810099  0.73690908]
[-1.20093113 -0.50979612]
[ 0.68068169  0.27301877]
[-1.39899564 -0.42281668]
[ 0.18552042  0.1570462 ]
[-0.50770535 -1.20563157]
[ 0.58164944  2.01260742]
[-1.59706014 -1.49556302]
[-0.50770535 -0.53878926]
[ 0.48261718  1.83864855]
[-1.39899564 -1.089659  ]
[ 0.77971394 -1.37959044]
[-0.30964085 -0.42281668]
[ 1.57197197  0.99784738]
[ 0.97777845  1.43274454]
[-0.30964085 -0.48080297]
[-0.11157634  2.15757314]
[-1.49802789 -0.1038921 ]
[-0.11157634  1.95462113]
[-0.70576986 -0.33583725]
```

```
[-0.50770535 -0.8287207 ]
[ 0.68068169 -1.37959044]
[-0.80480212 -1.58254245]
[-1.89415691 -1.46656987]
[ 1.07681071  0.12805305]
[ 0.08648817  1.51972397]
[-0.30964085  0.09905991]
[ 0.08648817  0.04107362]
[-1.39899564 -1.3505973 ]
[ 0.28455268  0.07006676]
[-0.90383437  0.38899135]
[ 1.57197197 -1.26361786]
[-0.30964085 -0.74174127]
[-0.11157634  0.1570462 ]
[-0.90383437 -0.65476184]
[-0.70576986 -0.04590581]
[ 0.38358493 -0.45180983]
[-0.80480212  1.89663484]
[ 1.37390747  1.28777882]
[ 1.17584296 -0.97368642]
[ 1.77003648  1.83864855]
[-0.90383437 -0.24885782]
[-0.80480212  0.56295021]
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[-0.50770535 -1.11865214]
[ 0.28455268  0.07006676]
[-0.21060859 -1.06066585]
[ 1.67100423  1.6067034 ]
[ 0.97777845  1.78066227]
[ 0.28455268  0.04107362]
[-0.80480212 -0.21986468]
[-0.11157634  0.07006676]
[ 0.28455268 -0.19087153]
[ 1.96810099 -0.65476184]
[-0.80480212  1.3457651 ]
[-1.79512465 -0.59677555]
[-0.11157634  0.12805305]
[ 0.28455268 -0.30684411]
[ 1.07681071  0.56295021]
[-1.00286662  0.27301877]
[ 1.47293972  0.35999821]
[ 0.18552042 -0.3648304 ]
[ 2.1661655  -1.03167271]
[-0.30964085  1.11381995]
[-1.6960924   0.07006676]
[-0.01254409  0.04107362]
[ 0.08648817  1.05583366]
[-0.11157634 -0.3648304 ]
[-1.20093113  0.07006676]
[-0.30964085 -1.3505973 ]
[ 1.57197197  1.11381995]
[-0.80480212 -1.52455616]
[ 0.08648817  1.8676417 ]
[-0.90383437 -0.77073441]
[-0.50770535 -0.77073441]
[-0.30964085 -0.91570013]
[ 0.28455268 -0.71274813]
[ 0.28455268  0.07006676]
[ 0.08648817  1.8676417 ]
[-1.10189888  1.95462113]
[-1.6960924  -1.5535493 ]
[-1.20093113 -1.089659  ]
[-0.70576986 -0.1038921 ]
[ 0.08648817  0.09905991]
[ 0.28455268  0.27301877]
[ 0.8787462  -0.5677824 ]
[ 0.28455268 -1.14764529]
[-0.11157634  0.67892279]
[ 2.1661655  -0.68375498]
[-1.29996338 -1.37959044]
[-1.00286662 -0.94469328]
[-0.01254409 -0.42281668]
[-0.21060859 -0.45180983]
[-1.79512465 -0.97368642]
[ 1.77003648  0.99784738]
[ 0.18552042 -0.3648304 ]
[ 0.38358493  1.11381995]
[-1.79512465 -1.3505973 ]
[ 0.18552042 -0.13288524]
[ 0.8787462  -1.43757673]
[-1.99318916  0.47597078]
[-0.30964085  0.27301877]
[ 1.86906873 -1.06066585]
```

```
 [-0.4086731   0.07006676]
 [ 1.07681071 -0.88670699]
 [-1.10189888 -1.11865214]
 [-1.89415691  0.01208048]
 [ 0.08648817  0.27301877]
 [-1.20093113  0.33100506]
 [-1.29996338  0.30201192]
 [-1.00286662  0.44697764]
 [ 1.67100423 -0.88670699]
 [ 1.17584296  0.53395707]
 [ 1.07681071  0.53395707]
 [ 1.37390747  2.331532  ]
 [-0.30964085 -0.13288524]
 [ 0.38358493 -0.45180983]
 [-0.4086731  -0.77073441]
 [-0.11157634 -0.50979612]
 [ 0.97777845 -1.14764529]
 [-0.90383437 -0.77073441]
 [-0.21060859 -0.50979612]
 [-1.10189888 -0.45180983]
 [-1.20093113  1.40375139]]
```

In [24]:
```
print(X_test)
```

```
[[-0.80480212  0.50496393]
 [-0.01254409 -0.5677824 ]
 [-0.30964085  0.1570462 ]
 [-0.80480212  0.27301877]
 [-0.30964085 -0.5677824 ]
 [-1.10189888 -1.43757673]
 [-0.70576986 -1.58254245]
 [-0.21060859  2.15757314]
 [-1.99318916 -0.04590581]
 [ 0.8787462  -0.77073441]
 [-0.80480212 -0.59677555]
 [-1.00286662 -0.42281668]
 [-0.11157634 -0.42281668]
 [ 0.08648817  0.21503249]
 [-1.79512465  0.47597078]
 [-0.60673761  1.37475825]
 [-0.11157634  0.21503249]
 [-1.89415691  0.44697764]
 [ 1.67100423  1.75166912]
 [-0.30964085 -1.37959044]
 [-0.30964085 -0.65476184]
 [ 0.8787462   2.15757314]
 [ 0.28455268 -0.53878926]
 [ 0.8787462   1.02684052]
 [-1.49802789 -1.20563157]
 [ 1.07681071  2.07059371]
 [-1.00286662  0.50496393]
 [-0.90383437  0.30201192]
 [-0.11157634 -0.21986468]
 [-0.60673761  0.47597078]
 [-1.6960924   0.53395707]
 [-0.11157634  0.27301877]
 [ 1.86906873 -0.27785096]
 [-0.11157634 -0.48080297]
 [-1.39899564 -0.33583725]
 [-1.99318916 -0.50979612]
 [-1.59706014  0.33100506]
 [-0.4086731  -0.77073441]
 [-0.70576986 -1.03167271]
 [ 1.07681071 -0.97368642]
 [-1.10189888  0.53395707]
 [ 0.28455268 -0.50979612]
 [-1.10189888  0.41798449]
 [-0.30964085 -1.43757673]
 [ 0.48261718  1.22979253]
 [-1.10189888 -0.33583725]
 [-0.11157634  0.30201192]
 [ 1.37390747  0.59194336]
 [-1.20093113 -1.14764529]
 [ 1.07681071  0.47597078]
 [ 1.86906873  1.51972397]
 [-0.4086731  -1.29261101]
 [-0.30964085 -0.3648304 ]
 [-0.4086731   1.31677196]
 [ 2.06713324  0.53395707]
 [ 0.68068169 -1.089659  ]
 [-0.90383437  0.38899135]
```

```
 [-1.20093113  0.30201192]
 [ 1.07681071 -1.20563157]
 [-1.49802789 -1.43757673]
 [-0.60673761 -1.49556302]
 [ 2.1661655  -0.79972756]
 [-1.89415691  0.18603934]
 [-0.21060859  0.85288166]
 [-1.89415691 -1.26361786]
 [ 2.1661655   0.38899135]
 [-1.39899564  0.56295021]
 [-1.10189888 -0.33583725]
 [ 0.18552042 -0.65476184]
 [ 0.38358493  0.01208048]
 [-0.60673761  2.331532  ]
 [-0.30964085  0.21503249]
 [-1.59706014 -0.19087153]
 [ 0.68068169 -1.37959044]
 [-1.10189888  0.56295021]
 [-1.99318916  0.35999821]
 [ 0.38358493  0.27301877]
 [ 0.18552042 -0.27785096]
 [ 1.47293972 -1.03167271]
 [ 0.8787462   1.08482681]
 [ 1.96810099  2.15757314]
 [ 2.06713324  0.38899135]
 [-1.39899564 -0.42281668]
 [-1.20093113 -1.00267957]
 [ 1.96810099 -0.91570013]
 [ 0.38358493  0.30201192]
 [ 0.18552042  0.1570462 ]
 [ 2.06713324  1.75166912]
 [ 0.77971394 -0.8287207 ]
 [ 0.28455268 -0.27785096]
 [ 0.38358493 -0.16187839]
 [-0.11157634  2.21555943]
 [-1.49802789 -0.62576869]
 [-1.29996338 -1.06066585]
 [-1.39899564  0.41798449]
 [-1.10189888  0.76590222]
 [-1.49802789 -0.19087153]
 [ 0.97777845 -1.06066585]
 [ 0.97777845  0.59194336]
 [ 0.38358493  0.99784738]]
```

Training the SVM model on the Training set

In [25]:
```
from sklearn.svm import SVC
classifier = SVC(kernel = 'linear', random_state = 0)
classifier.fit(X_train, y_train)
```

Out[25]:
```
SVC(kernel='linear', random_state=0)
```

Predicting a new result

In [26]:
```
print(classifier.predict(sc.transform([[30,87000]])))
```

```
[0]
```

Predicting the Test set results

In [27]:
```
y_pred = classifier.predict(X_test)
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]
```

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

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

Making the Confusion Matrix

In [28]:

```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

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

Out[28]:

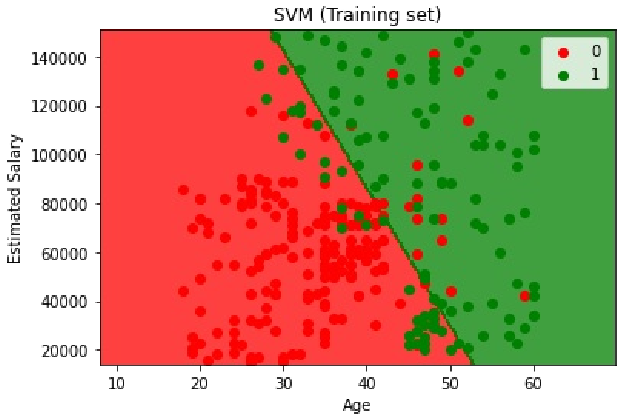
```
0.9
```

Visualising the Training set results

In [15]:

```
from matplotlib.colors import ListedColormap
X_set, y_set = sc.inverse_transform(X_train), y_train
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))
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')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
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)
plt.title('SVM (Training set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.
```



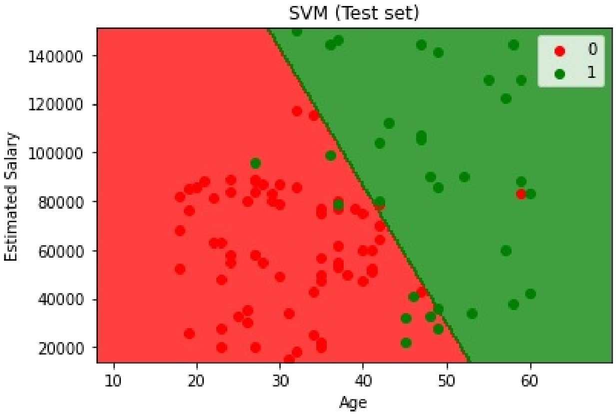
Visualising the Test set results

In [16]:

```
from matplotlib.colors import ListedColormap
X_set, y_set = sc.inverse_transform(X_test), y_test
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))
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')))
plt.xlim(X1.min(), X1.max())
```

```
plt.ylim(X2.min(), X2.max())
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)
plt.title('SVM (Test set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.
```



Practical No - 4 : Naive Bayes

Importing the libraries

In [0]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

Importing the dataset

In [0]:
```
dataset = pd.read_csv('Social_Network_Ads.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
```

Splitting the dataset into the Training set and Test set

In [0]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)
```

In [4]:
```
print(X_train)
```

```
[[    44  39000]
 [    32 120000]
 [    38  50000]
 [    32 135000]
 [    52  21000]
 [    53 104000]
 [    39  42000]
 [    38  61000]
 [    36  50000]
 [    36  63000]
 [    35  25000]
 [    35  50000]
 [    42  73000]
 [    47  49000]
 [    59  29000]
 [    49  65000]
 [    45 131000]
 [    31  89000]
 [    46  82000]
 [    47  51000]
 [    26  15000]
 [    60 102000]
 [    38 112000]
 [    40 107000]
 [    42  53000]
 [    35  59000]
 [    48  41000]
 [    48 134000]
 [    38 113000]
 [    29 148000]
 [    26  15000]
 [    60  42000]
 [    24  19000]
 [    42 149000]
 [    46  96000]
 [    28  59000]
 [    39  96000]
 [    28  89000]
 [    41  72000]
 [    45  26000]
 [    33  69000]
 [    20  82000]
 [    31  74000]
 [    42  80000]
 [    35  72000]
 [    33 149000]
 [    40  71000]
 [    51 146000]
 [    46  79000]
 [    35  75000]
 [    38  51000]
 [    36  75000]
 [    37  78000]
 [    38  61000]
```

```
 [    60 108000]
 [    20  82000]
 [    57  74000]
 [    42  65000]
 [    26  80000]
 [    46 117000]
 [    35  61000]
 [    21  68000]
 [    28  44000]
 [    41  87000]
 [    37  33000]
 [    27  90000]
 [    39  42000]
 [    28 123000]
 [    31 118000]
 [    25  87000]
 [    35  71000]
 [    37  70000]
 [    35  39000]
 [    47  23000]
 [    35 147000]
 [    48 138000]
 [    26  86000]
 [    25  79000]
 [    52 138000]
 [    51  23000]
 [    35  60000]
 [    33 113000]
 [    30 107000]
 [    48  33000]
 [    41  80000]
 [    48  96000]
 [    31  18000]
 [    31  71000]
 [    43 129000]
 [    59  76000]
 [    18  44000]
 [    36 118000]
 [    42  90000]
 [    47  30000]
 [    26  43000]
 [    40  78000]
 [    46  59000]
 [    59  42000]
 [    46  74000]
 [    35  91000]
 [    28  59000]
 [    40  57000]
 [    59 143000]
 [    57  26000]
 [    52  38000]
 [    47 113000]
 [    53 143000]
 [    35  27000]
 [    58 101000]
 [    45  45000]
 [    23  82000]
 [    46  23000]
 [    42  65000]
 [    28  84000]
 [    38  59000]
 [    26  84000]
 [    29  28000]
 [    37  71000]
 [    22  55000]
 [    48  35000]
 [    49  28000]
 [    38  65000]
 [    27  17000]
 [    46  28000]
 [    48 141000]
 [    26  17000]
 [    35  97000]
 [    39  59000]
 [    24  27000]
 [    32  18000]
 [    46  88000]
 [    35  58000]
 [    56  60000]
 [    47  34000]
 [    40  72000]
 [    32 100000]
 [    19  21000]
```

```
[    25  90000]
[    35  88000]
[    28  32000]
[    50  20000]
[    40  59000]
[    50  44000]
[    35  72000]
[    40 142000]
[    46  32000]
[    39  71000]
[    20  74000]
[    29  75000]
[    31  76000]
[    47  25000]
[    40  61000]
[    34 112000]
[    38  80000]
[    42  75000]
[    47  47000]
[    39  75000]
[    19  25000]
[    37  80000]
[    36  60000]
[    41  52000]
[    36 125000]
[    48  29000]
[    36 126000]
[    51 134000]
[    27  57000]
[    38  71000]
[    39  61000]
[    22  27000]
[    33  60000]
[    48  74000]
[    58  23000]
[    53  72000]
[    32 117000]
[    54  70000]
[    30  80000]
[    58  95000]
[    26  52000]
[    45  79000]
[    24  55000]
[    40  75000]
[    33  28000]
[    44 139000]
[    22  18000]
[    33  51000]
[    43 133000]
[    24  32000]
[    46  22000]
[    35  55000]
[    54 104000]
[    48 119000]
[    35  53000]
[    37 144000]
[    23  66000]
[    37 137000]
[    31  58000]
[    33  41000]
[    45  22000]
[    30  15000]
[    19  19000]
[    49  74000]
[    39 122000]
[    35  73000]
[    39  71000]
[    24  23000]
[    41  72000]
[    29  83000]
[    54  26000]
[    35  44000]
[    37  75000]
[    29  47000]
[    31  68000]
[    42  54000]
[    30 135000]
[    52 114000]
[    50  36000]
[    56 133000]
[    29  61000]
[    30  89000]
[    26  16000]
```

```
 [    33  31000]
 [    41  72000]
 [    36  33000]
 [    55 125000]
 [    48 131000]
 [    41  71000]
 [    30  62000]
 [    37  72000]
 [    41  63000]
 [    58  47000]
 [    30 116000]
 [    20  49000]
 [    37  74000]
 [    41  59000]
 [    49  89000]
 [    28  79000]
 [    53  82000]
 [    40  57000]
 [    60  34000]
 [    35 108000]
 [    21  72000]
 [    38  71000]
 [    39 106000]
 [    37  57000]
 [    26  72000]
 [    35  23000]
 [    54 108000]
 [    30  17000]
 [    39 134000]
 [    29  43000]
 [    33  43000]
 [    35  38000]
 [    41  45000]
 [    41  72000]
 [    39 134000]
 [    27 137000]
 [    21  16000]
 [    26  32000]
 [    31  66000]
 [    39  73000]
 [    41  79000]
 [    47  50000]
 [    41  30000]
 [    37  93000]
 [    60  46000]
 [    25  22000]
 [    28  37000]
 [    38  55000]
 [    36  54000]
 [    20  36000]
 [    56 104000]
 [    40  57000]
 [    42 108000]
 [    20  23000]
 [    40  65000]
 [    47  20000]
 [    18  86000]
 [    35  79000]
 [    57  33000]
 [    34  72000]
 [    49  39000]
 [    27  31000]
 [    19  70000]
 [    39  79000]
 [    26  81000]
 [    25  80000]
 [    28  85000]
 [    55  39000]
 [    50  88000]
 [    49  88000]
 [    52 150000]
 [    35  65000]
 [    42  54000]
 [    34  43000]
 [    37  52000]
 [    48  30000]
 [    29  43000]
 [    36  52000]
 [    27  54000]
 [    26 118000]]
```

In [5]:

```
print(y_train)
```

```
In [5]: print(y_train)
```

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

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

```
[[    30  87000]
 [    38  50000]
 [    35  75000]
 [    30  79000]
 [    35  50000]
 [    27  20000]
 [    31  15000]
 [    36 144000]
 [    18  68000]
 [    47  43000]
 [    30  49000]
 [    28  55000]
 [    37  55000]
 [    39  77000]
 [    20  86000]
 [    32 117000]
 [    37  77000]
 [    19  85000]
 [    55 130000]
 [    35  22000]
 [    35  47000]
 [    47 144000]
 [    41  51000]
 [    47 105000]
 [    23  28000]
 [    49 141000]
 [    28  87000]
 [    29  80000]
 [    37  62000]
 [    32  86000]
 [    21  88000]
 [    37  79000]
 [    57  60000]
 [    37  53000]
 [    24  58000]
 [    18  52000]
 [    22  81000]
 [    34  43000]
 [    31  34000]
 [    49  36000]
 [    27  88000]
 [    41  52000]
 [    27  84000]
 [    35  20000]
 [    43 112000]
 [    27  58000]
 [    37  80000]
 [    52  90000]
 [    26  30000]
 [    49  86000]
 [    57 122000]
 [    34  25000]
 [    35  57000]
 [    34 115000]
 [    59  88000]
 [    45  32000]
 [    29  83000]
 [    26  80000]
 [    49  28000]
 [    23  20000]
 [    32  18000]
 [    60  42000]
 [    19  76000]
 [    36  99000]
 [    19  26000]
 [    60  83000]
 [    24  89000]
 [    27  58000]
```

```
 [    40  47000]
 [    42  70000]
 [    32 150000]
 [    35  77000]
 [    22  63000]
 [    45  22000]
 [    27  89000]
 [    18  82000]
 [    42  79000]
 [    40  60000]
 [    53  34000]
 [    47 107000]
 [    58 144000]
 [    59  83000]
 [    24  55000]
 [    26  35000]
 [    58  38000]
 [    42  80000]
 [    40  75000]
 [    59 130000]
 [    46  41000]
 [    41  60000]
 [    42  64000]
 [    37 146000]
 [    23  48000]
 [    25  33000]
 [    24  84000]
 [    27  96000]
 [    23  63000]
 [    48  33000]
 [    48  90000]
 [    42 104000]]
```

In [7]:

```
print(y_test)
```

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

Feature Scaling

In [8]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [9]:

```
print(X_train)
```

```
[[ 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]
[-1.20093113  0.30201192]
[ 0.77971394  1.37475825]
[-0.30964085 -0.24885782]
[-1.6960924  -0.04590581]
[-1.00286662 -0.74174127]
[ 0.28455268  0.50496393]
[-0.11157634 -1.06066585]
[-1.10189888  0.59194336]
[ 0.08648817 -0.79972756]
[-1.00286662  1.54871711]
[-0.70576986  1.40375139]
[-1.29996338  0.50496393]
[-0.30964085  0.04107362]
[-0.11157634  0.01208048]
[-0.30964085 -0.88670699]
[ 0.8787462  -1.3505973 ]
[-0.30964085  2.24455257]
[ 0.97777845  1.98361427]
[-1.20093113  0.47597078]
[-1.29996338  0.27301877]
[ 1.37390747  1.98361427]
[ 1.27487521 -1.3505973 ]
[-0.30964085 -0.27785096]
[-0.50770535  1.25878567]
[-0.80480212  1.08482681]
[ 0.97777845 -1.06066585]
[ 0.28455268  0.30201192]
[ 0.97777845  0.76590222]
[-0.70576986 -1.49556302]
[-0.70576986  0.04107362]
[ 0.48261718  1.72267598]
[ 2.06713324  0.18603934]
[-1.99318916 -0.74174127]
[-0.21060859  1.40375139]
[ 0.38358493  0.59194336]
[ 0.8787462  -1.14764529]
[-1.20093113 -0.77073441]
[ 0.18552042  0.24402563]
[ 0.77971394 -0.30684411]
[ 2.06713324 -0.79972756]
[ 0.77971394  0.12805305]
[-0.30964085  0.6209365 ]
[-1.00286662 -0.30684411]
[ 0.18552042 -0.3648304 ]
[ 2.06713324  2.12857999]
[ 1.86906873 -1.26361786]
[ 1.37390747 -0.91570013]
[ 0.8787462   1.25878567]
[ 1.47293972  2.12857999]
[-0.30964085 -1.23462472]
[ 1.96810099  0.91086794]
[ 0.68068169 -0.71274813]
[-1.49802789  0.35999821]
[ 0.77971394 -1.3505973 ]
[ 0.38358493 -0.13288524]
```

```
 [-1.00286662  0.41798449]
 [-0.01254409 -0.30684411]
 [-1.20093113  0.41798449]
 [-0.90383437 -1.20563157]
 [-0.11157634  0.04107362]
 [-1.59706014 -0.42281668]
 [ 0.97777845 -1.00267957]
 [ 1.07681071 -1.20563157]
 [-0.01254409 -0.13288524]
 [-1.10189888 -1.52455616]
 [ 0.77971394 -1.20563157]
 [ 0.97777845  2.07059371]
 [-1.20093113 -1.52455616]
 [-0.30964085  0.79489537]
 [ 0.08648817 -0.30684411]
 [-1.39899564 -1.23462472]
 [-0.60673761 -1.49556302]
 [ 0.77971394  0.53395707]
 [-0.30964085 -0.33583725]
 [ 1.77003648 -0.27785096]
 [ 0.8787462  -1.03167271]
 [ 0.18552042  0.07006676]
 [-0.60673761  0.8818748 ]
 [-1.89415691 -1.40858358]
 [-1.29996338  0.59194336]
 [-0.30964085  0.53395707]
 [-1.00286662 -1.089659  ]
 [ 1.17584296 -1.43757673]
 [ 0.18552042 -0.30684411]
 [ 1.17584296 -0.74174127]
 [-0.30964085  0.07006676]
 [ 0.18552042  2.09958685]
 [ 0.77971394 -1.089659  ]
 [ 0.08648817  0.04107362]
 [-1.79512465  0.12805305]
 [-0.90383437  0.1570462 ]
 [-0.70576986  0.18603934]
 [ 0.8787462  -1.29261101]
 [ 0.18552042 -0.24885782]
 [-0.4086731   1.22979253]
 [-0.01254409  0.30201192]
 [ 0.38358493  0.1570462 ]
 [ 0.8787462  -0.65476184]
 [ 0.08648817  0.1570462 ]
 [-1.89415691 -1.29261101]
 [-0.11157634  0.30201192]
 [-0.21060859 -0.27785096]
 [ 0.28455268 -0.50979612]
 [-0.21060859  1.6067034 ]
 [ 0.97777845 -1.17663843]
 [-0.21060859  1.63569655]
 [ 1.27487521  1.8676417 ]
 [-1.10189888 -0.3648304 ]
 [-0.01254409  0.04107362]
 [ 0.08648817 -0.24885782]
 [-1.59706014 -1.23462472]
 [-0.50770535 -0.27785096]
 [ 0.97777845  0.12805305]
 [ 1.96810099 -1.3505973 ]
 [ 1.47293972  0.07006676]
 [-0.60673761  1.37475825]
 [ 1.57197197  0.01208048]
 [-0.80480212  0.30201192]
 [ 1.96810099  0.73690908]
 [-1.20093113 -0.50979612]
 [ 0.68068169  0.27301877]
 [-1.39899564 -0.42281668]
 [ 0.18552042  0.1570462 ]
 [-0.50770535 -1.20563157]
 [ 0.58164944  2.01260742]
 [-1.59706014 -1.49556302]
 [-0.50770535 -0.53878926]
 [ 0.48261718  1.83864855]
 [-1.39899564 -1.089659  ]
 [ 0.77971394 -1.37959044]
 [-0.30964085 -0.42281668]
 [ 1.57197197  0.99784738]
 [ 0.97777845  1.43274454]
 [-0.30964085 -0.48080297]
 [-0.11157634  2.15757314]
 [-1.49802789 -0.1038921 ]
 [-0.11157634  1.95462113]
 [-0.70576986 -0.33583725]
```

```
[-0.50770535 -0.8287207 ]
[ 0.68068169 -1.37959044]
[-0.80480212 -1.58254245]
[-1.89415691 -1.46656987]
[ 1.07681071  0.12805305]
[ 0.08648817  1.51972397]
[-0.30964085  0.09905991]
[ 0.08648817  0.04107362]
[-1.39899564 -1.3505973 ]
[ 0.28455268  0.07006676]
[-0.90383437  0.38899135]
[ 1.57197197 -1.26361786]
[-0.30964085 -0.74174127]
[-0.11157634  0.1570462 ]
[-0.90383437 -0.65476184]
[-0.70576986 -0.04590581]
[ 0.38358493 -0.45180983]
[-0.80480212  1.89663484]
[ 1.37390747  1.28777882]
[ 1.17584296 -0.97368642]
[ 1.77003648  1.83864855]
[-0.90383437 -0.24885782]
[-0.80480212  0.56295021]
[-1.20093113 -1.5535493 ]
[-0.50770535 -1.11865214]
[ 0.28455268  0.07006676]
[-0.21060859 -1.06066585]
[ 1.67100423  1.6067034 ]
[ 0.97777845  1.78066227]
[ 0.28455268  0.04107362]
[-0.80480212 -0.21986468]
[-0.11157634  0.07006676]
[ 0.28455268 -0.19087153]
[ 1.96810099 -0.65476184]
[-0.80480212  1.3457651 ]
[-1.79512465 -0.59677555]
[-0.11157634  0.12805305]
[ 0.28455268 -0.30684411]
[ 1.07681071  0.56295021]
[-1.00286662  0.27301877]
[ 1.47293972  0.35999821]
[ 0.18552042 -0.3648304 ]
[ 2.1661655  -1.03167271]
[-0.30964085  1.11381995]
[-1.6960924   0.07006676]
[-0.01254409  0.04107362]
[ 0.08648817  1.05583366]
[-0.11157634 -0.3648304 ]
[-1.20093113  0.07006676]
[-0.30964085 -1.3505973 ]
[ 1.57197197  1.11381995]
[-0.80480212 -1.52455616]
[ 0.08648817  1.8676417 ]
[-0.90383437 -0.77073441]
[-0.50770535 -0.77073441]
[-0.30964085 -0.91570013]
[ 0.28455268 -0.71274813]
[ 0.28455268  0.07006676]
[ 0.08648817  1.8676417 ]
[-1.10189888  1.95462113]
[-1.6960924  -1.5535493 ]
[-1.20093113 -1.089659  ]
[-0.70576986 -0.1038921 ]
[ 0.08648817  0.09905991]
[ 0.28455268  0.27301877]
[ 0.8787462  -0.5677824 ]
[ 0.28455268 -1.14764529]
[-0.11157634  0.67892279]
[ 2.1661655  -0.68375498]
[-1.29996338 -1.37959044]
[-1.00286662 -0.94469328]
[-0.01254409 -0.42281668]
[-0.21060859 -0.45180983]
[-1.79512465 -0.97368642]
[ 1.77003648  0.99784738]
[ 0.18552042 -0.3648304 ]
[ 0.38358493  1.11381995]
[-1.79512465 -1.3505973 ]
[ 0.18552042 -0.13288524]
[ 0.8787462  -1.43757673]
[-1.99318916  0.47597078]
[-0.30964085  0.27301877]
[ 1.86906873 -1.06066585]
```

```
 [-0.4086731   0.07006676]
 [ 1.07681071 -0.88670699]
 [-1.10189888 -1.11865214]
 [-1.89415691  0.01208048]
 [ 0.08648817  0.27301877]
 [-1.20093113  0.33100506]
 [-1.29996338  0.30201192]
 [-1.00286662  0.44697764]
 [ 1.67100423 -0.88670699]
 [ 1.17584296  0.53395707]
 [ 1.07681071  0.53395707]
 [ 1.37390747  2.331532  ]
 [-0.30964085 -0.13288524]
 [ 0.38358493 -0.45180983]
 [-0.4086731  -0.77073441]
 [-0.11157634 -0.50979612]
 [ 0.97777845 -1.14764529]
 [-0.90383437 -0.77073441]
 [-0.21060859 -0.50979612]
 [-1.10189888 -0.45180983]
 [-1.20093113  1.40375139]]
```

In [10]:

```python
print(X_test)
```

```
[[-0.80480212  0.50496393]
 [-0.01254409 -0.5677824 ]
 [-0.30964085  0.1570462 ]
 [-0.80480212  0.27301877]
 [-0.30964085 -0.5677824 ]
 [-1.10189888 -1.43757673]
 [-0.70576986 -1.58254245]
 [-0.21060859  2.15757314]
 [-1.99318916 -0.04590581]
 [ 0.8787462  -0.77073441]
 [-0.80480212 -0.59677555]
 [-1.00286662 -0.42281668]
 [-0.11157634 -0.42281668]
 [ 0.08648817  0.21503249]
 [-1.79512465  0.47597078]
 [-0.60673761  1.37475825]
 [-0.11157634  0.21503249]
 [-1.89415691  0.44697764]
 [ 1.67100423  1.75166912]
 [-0.30964085 -1.37959044]
 [-0.30964085 -0.65476184]
 [ 0.8787462   2.15757314]
 [ 0.28455268 -0.53878926]
 [ 0.8787462   1.02684052]
 [-1.49802789 -1.20563157]
 [ 1.07681071  2.07059371]
 [-1.00286662  0.50496393]
 [-0.90383437  0.30201192]
 [-0.11157634 -0.21986468]
 [-0.60673761  0.47597078]
 [-1.6960924   0.53395707]
 [-0.11157634  0.27301877]
 [ 1.86906873 -0.27785096]
 [-0.11157634 -0.48080297]
 [-1.39899564 -0.33583725]
 [-1.99318916 -0.50979612]
 [-1.59706014  0.33100506]
 [-0.4086731  -0.77073441]
 [-0.70576986 -1.03167271]
 [ 1.07681071 -0.97368642]
 [-1.10189888  0.53395707]
 [ 0.28455268 -0.50979612]
 [-1.10189888  0.41798449]
 [-0.30964085 -1.43757673]
 [ 0.48261718  1.22979253]
 [-1.10189888 -0.33583725]
 [-0.11157634  0.30201192]
 [ 1.37390747  0.59194336]
 [-1.20093113 -1.14764529]
 [ 1.07681071  0.47597078]
 [ 1.86906873  1.51972397]
 [-0.4086731  -1.29261101]
 [-0.30964085 -0.3648304 ]
 [-0.4086731   1.31677196]
 [ 2.06713324  0.53395707]
 [ 0.68068169 -1.089659  ]
 [-0.90383437  0.38899135]
```

```
 [-1.20093113  0.30201192]
 [ 1.07681071 -1.20563157]
 [-1.49802789 -1.43757673]
 [-0.60673761 -1.49556302]
 [ 2.1661655  -0.79972756]
 [-1.89415691  0.18603934]
 [-0.21060859  0.85288166]
 [-1.89415691 -1.26361786]
 [ 2.1661655   0.38899135]
 [-1.39899564  0.56295021]
 [-1.10189888 -0.33583725]
 [ 0.18552042 -0.65476184]
 [ 0.38358493  0.01208048]
 [-0.60673761  2.331532  ]
 [-0.30964085  0.21503249]
 [-1.59706014 -0.19087153]
 [ 0.68068169 -1.37959044]
 [-1.10189888  0.56295021]
 [-1.99318916  0.35999821]
 [ 0.38358493  0.27301877]
 [ 0.18552042 -0.27785096]
 [ 1.47293972 -1.03167271]
 [ 0.8787462   1.08482681]
 [ 1.96810099  2.15757314]
 [ 2.06713324  0.38899135]
 [-1.39899564 -0.42281668]
 [-1.20093113 -1.00267957]
 [ 1.96810099 -0.91570013]
 [ 0.38358493  0.30201192]
 [ 0.18552042  0.1570462 ]
 [ 2.06713324  1.75166912]
 [ 0.77971394 -0.8287207 ]
 [ 0.28455268 -0.27785096]
 [ 0.38358493 -0.16187839]
 [-0.11157634  2.21555943]
 [-1.49802789 -0.62576869]
 [-1.29996338 -1.06066585]
 [-1.39899564  0.41798449]
 [-1.10189888  0.76590222]
 [-1.49802789 -0.19087153]
 [ 0.97777845 -1.06066585]
 [ 0.97777845  0.59194336]
 [ 0.38358493  0.99784738]]
```

Training the Naive Bayes model on the Training set

In [11]:

```
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)
```

Out[11]:

```
GaussianNB(priors=None, var_smoothing=1e-09)
```

Predicting a new result

In [12]:

```
print(classifier.predict(sc.transform([[30,87000]])))
```

```
[0]
```

Predicting the Test set results

In [13]:

```
y_pred = classifier.predict(X_test)
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]
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[0 1]
[1 1]
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[1 1]
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[0 1]
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[0 0]
[0 0]
[0 0]
[1 1]
[1 1]
[1 1]
[1 0]
[0 0]
[0 0]
[1 1]
[0 1]
[0 0]
[1 1]
[0 1]
[0 0]
[0 0]
[1 1]
```

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

Making the Confusion Matrix

In [14]:
```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

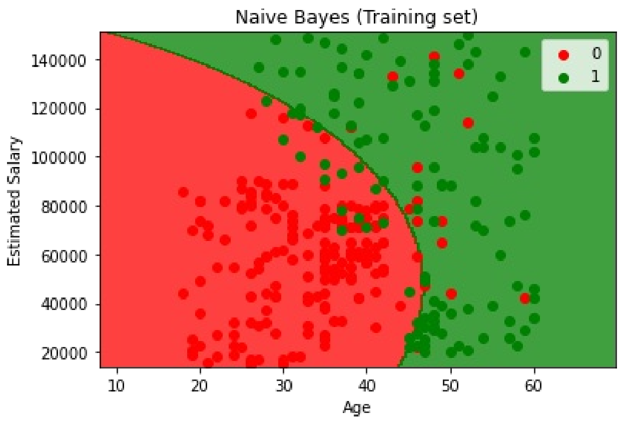
```
[[65  3]
 [ 7 25]]
```

Out[14]:
```
0.9
```

Visualising the Training set results

In [15]:
```
from matplotlib.colors import ListedColormap
X_set, y_set = sc.inverse_transform(X_train), y_train
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))
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')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())
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)
plt.title('Naive Bayes (Training set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have
precedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you really wan
t to specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have
precedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you really wan
t to specify the same RGB or RGBA value for all points.
```

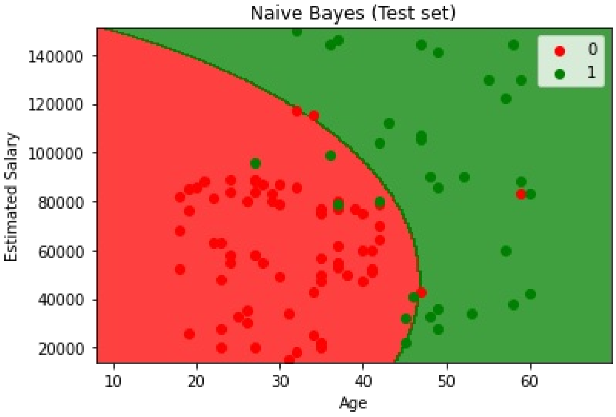


Visualising the Test set results

In [16]:
```
from matplotlib.colors import ListedColormap
X_set, y_set = sc.inverse_transform(X_test), y_test
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))
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')))
plt.xlim(X1.min(), X1.max())
```

```
plt.ylim(X2.min(), X2.max())
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)
plt.title('Naive Bayes (Test set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.
```



Practical No - 5 : K-Means Clustering

Importing the libraries

In [21]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

Importing the dataset

In [22]:
```
dataset = pd.read_csv('Mall_Customers.csv')
X = dataset.iloc[:, [3, 4]].values
X
```

Out[22]:
```
array([[ 15,  39],
       [ 15,  81],
       [ 16,   6],
       [ 16,  77],
       [ 17,  40],
       [ 17,  76],
       [ 18,   6],
       [ 18,  94],
       [ 19,   3],
       [ 19,  72],
       [ 19,  14],
       [ 19,  99],
       [ 20,  15],
       [ 20,  77],
       [ 20,  13],
       [ 20,  79],
       [ 21,  35],
       [ 21,  66],
       [ 23,  29],
       [ 23,  98],
       [ 24,  35],
       [ 24,  73],
       [ 25,   5],
       [ 25,  73],
       [ 28,  14],
       [ 28,  82],
       [ 28,  32],
       [ 28,  61],
       [ 29,  31],
       [ 29,  87],
       [ 30,   4],
       [ 30,  73],
       [ 33,   4],
       [ 33,  92],
       [ 33,  14],
       [ 33,  81],
       [ 34,  17],
       [ 34,  73],
       [ 37,  26],
       [ 37,  75],
       [ 38,  35],
       [ 38,  92],
       [ 39,  36],
       [ 39,  61],
       [ 39,  28],
       [ 39,  65],
       [ 40,  55],
       [ 40,  47],
       [ 40,  42],
       [ 40,  42],
       [ 42,  52],
       [ 42,  60],
       [ 43,  54],
       [ 43,  60],
       [ 43,  45],
       [ 43,  41],
       [ 44,  50],
       [ 44,  46],
       [ 46,  51],
       [ 46,  46],
       [ 46,  56],
       [ 46,  55],
       [ 47,  52],
```

```
[ 47,  59],
[ 48,  51],
[ 48,  59],
[ 48,  50],
[ 48,  48],
[ 48,  59],
[ 48,  47],
[ 49,  55],
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[ 63,  48],
[ 63,  52],
[ 63,  54],
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[ 64,  46],
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[ 65,  43],
[ 65,  59],
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[ 69,  91],
[ 70,  29],
[ 70,  77],
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[ 71,  95],
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[ 71,  75],
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[ 71,  75],
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[ 72,  71],
[ 73,   5],
[ 73,  88],
[ 73,   7],
[ 73,  73],
[ 74,  10],
[ 74,  72],
[ 75,   5],
[ 75,  93],
[ 76,  40],
[ 76,  87],
[ 77,  12],
[ 77,  97],
```
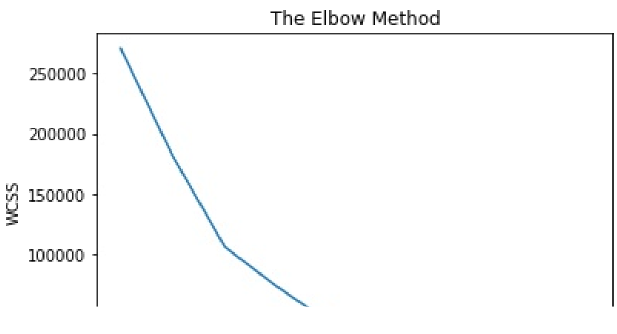
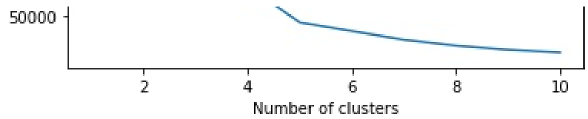

```
       [ 77,  36],
       [ 77,  74],
       [ 78,  22],
       [ 78,  90],
       [ 78,  17],
       [ 78,  88],
       [ 78,  20],
       [ 78,  76],
       [ 78,  16],
       [ 78,  89],
       [ 78,   1],
       [ 78,  78],
       [ 78,   1],
       [ 78,  73],
       [ 79,  35],
       [ 79,  83],
       [ 81,   5],
       [ 81,  93],
       [ 85,  26],
       [ 85,  75],
       [ 86,  20],
       [ 86,  95],
       [ 87,  27],
       [ 87,  63],
       [ 87,  13],
       [ 87,  75],
       [ 87,  10],
       [ 87,  92],
       [ 88,  13],
       [ 88,  86],
       [ 88,  15],
       [ 88,  69],
       [ 93,  14],
       [ 93,  90],
       [ 97,  32],
       [ 97,  86],
       [ 98,  15],
       [ 98,  88],
       [ 99,  39],
       [ 99,  97],
       [101,  24],
       [101,  68],
       [103,  17],
       [103,  85],
       [103,  23],
       [103,  69],
       [113,   8],
       [113,  91],
       [120,  16],
       [120,  79],
       [126,  28],
       [126,  74],
       [137,  18],
       [137,  83]], dtype=int64)
```

Using the elbow method to find the optimal number of clusters

In [23]:

```
from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```





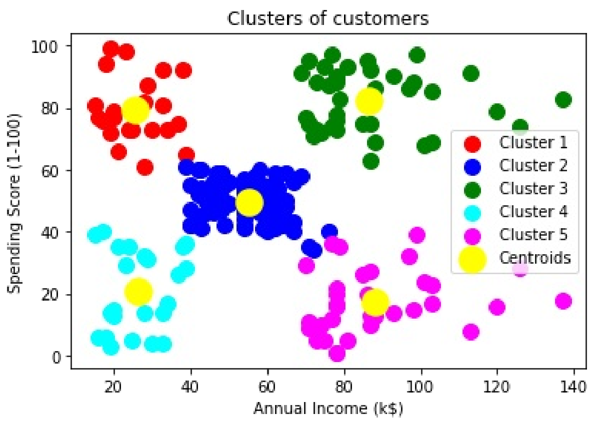
Training the K-Means model on the dataset

In [24]:
```
kmeans = KMeans(n_clusters = 5, init = 'k-means++', random_state = 42)
y_kmeans = kmeans.fit_predict(X)
y_kmeans
```

Out[24]:
```
array([3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0,
       3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 1,
       3, 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, 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, 4, 2, 1, 2, 4, 2, 4, 2,
       1, 2, 4, 2, 4, 2, 4, 2, 4, 2, 1, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2,
       4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2,
       4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2,
       4, 2])
```

Visualising the clusters

In [25]:
```
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 100, c = 'red', label = 'Cluster 1')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 100, c = 'blue', label = 'Cluster 2')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 100, c = 'green', label = 'Cluster 3')
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s = 100, c = 'cyan', label = 'Cluster 4')
plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], s = 100, c = 'magenta', label = 'Cluster 5')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'yellow', label = 'Centroi
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



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Practical No - 6 : Hierarchical Clustering

Importing the libraries

In [2]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

Importing the dataset

In [3]:
```
dataset = pd.read_csv('Mall_Customers.csv')
X = dataset.iloc[:, [3, 4]].values
X
```

Out[3]:
```
array([[ 15,  39],
       [ 15,  81],
       [ 16,   6],
       [ 16,  77],
       [ 17,  40],
       [ 17,  76],
       [ 18,   6],
       [ 18,  94],
       [ 19,   3],
       [ 19,  72],
       [ 19,  14],
       [ 19,  99],
       [ 20,  15],
       [ 20,  77],
       [ 20,  13],
       [ 20,  79],
       [ 21,  35],
       [ 21,  66],
       [ 23,  29],
       [ 23,  98],
       [ 24,  35],
       [ 24,  73],
       [ 25,   5],
       [ 25,  73],
       [ 28,  14],
       [ 28,  82],
       [ 28,  32],
       [ 28,  61],
       [ 29,  31],
       [ 29,  87],
       [ 30,   4],
       [ 30,  73],
       [ 33,   4],
       [ 33,  92],
       [ 33,  14],
       [ 33,  81],
       [ 34,  17],
       [ 34,  73],
       [ 37,  26],
       [ 37,  75],
       [ 38,  35],
       [ 38,  92],
       [ 39,  36],
       [ 39,  61],
       [ 39,  28],
       [ 39,  65],
       [ 40,  55],
       [ 40,  47],
       [ 40,  42],
       [ 40,  42],
       [ 42,  52],
       [ 42,  60],
       [ 43,  54],
       [ 43,  60],
       [ 43,  45],
       [ 43,  41],
       [ 44,  50],
       [ 44,  46],
       [ 46,  51],
       [ 46,  46],
       [ 46,  56],
       [ 46,  55],
       [ 47,  52],
```

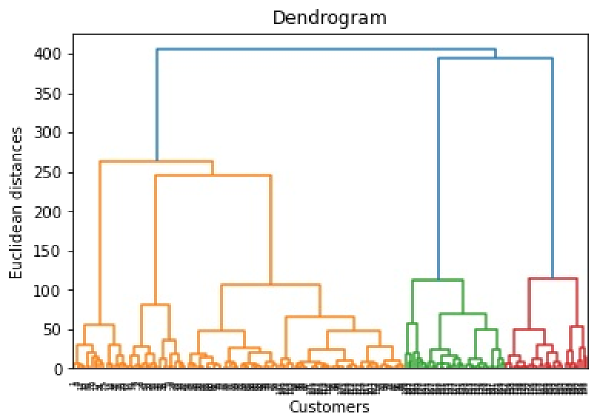
```
[ 47,  59],
[ 48,  51],
[ 48,  59],
[ 48,  50],
[ 48,  48],
[ 48,  59],
[ 48,  47],
[ 49,  55],
[ 49,  42],
[ 50,  49],
[ 50,  56],
[ 54,  47],
[ 54,  54],
[ 54,  53],
[ 54,  48],
[ 54,  52],
[ 54,  42],
[ 54,  51],
[ 54,  55],
[ 54,  41],
[ 54,  44],
[ 54,  57],
[ 54,  46],
[ 57,  58],
[ 57,  55],
[ 58,  60],
[ 58,  46],
[ 59,  55],
[ 59,  41],
[ 60,  49],
[ 60,  40],
[ 60,  42],
[ 60,  52],
[ 60,  47],
[ 60,  50],
[ 61,  42],
[ 61,  49],
[ 62,  41],
[ 62,  48],
[ 62,  59],
[ 62,  55],
[ 62,  56],
[ 62,  42],
[ 63,  50],
[ 63,  46],
[ 63,  43],
[ 63,  48],
[ 63,  52],
[ 63,  54],
[ 64,  42],
[ 64,  46],
[ 65,  48],
[ 65,  50],
[ 65,  43],
[ 65,  59],
[ 67,  43],
[ 67,  57],
[ 67,  56],
[ 67,  40],
[ 69,  58],
[ 69,  91],
[ 70,  29],
[ 70,  77],
[ 71,  35],
[ 71,  95],
[ 71,  11],
[ 71,  75],
[ 71,   9],
[ 71,  75],
[ 72,  34],
[ 72,  71],
[ 73,   5],
[ 73,  88],
[ 73,   7],
[ 73,  73],
[ 74,  10],
[ 74,  72],
[ 75,   5],
[ 75,  93],
[ 76,  40],
[ 76,  87],
[ 77,  12],
[ 77,  97],
```

```
       [ 77,  36],
       [ 77,  74],
       [ 78,  22],
       [ 78,  90],
       [ 78,  17],
       [ 78,  88],
       [ 78,  20],
       [ 78,  76],
       [ 78,  16],
       [ 78,  89],
       [ 78,   1],
       [ 78,  78],
       [ 78,   1],
       [ 78,  73],
       [ 79,  35],
       [ 79,  83],
       [ 81,   5],
       [ 81,  93],
       [ 85,  26],
       [ 85,  75],
       [ 86,  20],
       [ 86,  95],
       [ 87,  27],
       [ 87,  63],
       [ 87,  13],
       [ 87,  75],
       [ 87,  10],
       [ 87,  92],
       [ 88,  13],
       [ 88,  86],
       [ 88,  15],
       [ 88,  69],
       [ 93,  14],
       [ 93,  90],
       [ 97,  32],
       [ 97,  86],
       [ 98,  15],
       [ 98,  88],
       [ 99,  39],
       [ 99,  97],
       [101,  24],
       [101,  68],
       [103,  17],
       [103,  85],
       [103,  23],
       [103,  69],
       [113,   8],
       [113,  91],
       [120,  16],
       [120,  79],
       [126,  28],
       [126,  74],
       [137,  18],
       [137,  83]], dtype=int64)
```

Using the dendrogram to find the optimal number of clusters

In [5]:

```python
import scipy.cluster.hierarchy as sch
dendrogram = sch.dendrogram(sch.linkage(X, method = 'ward'))
plt.title('Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Euclidean distances')
plt.show()
```



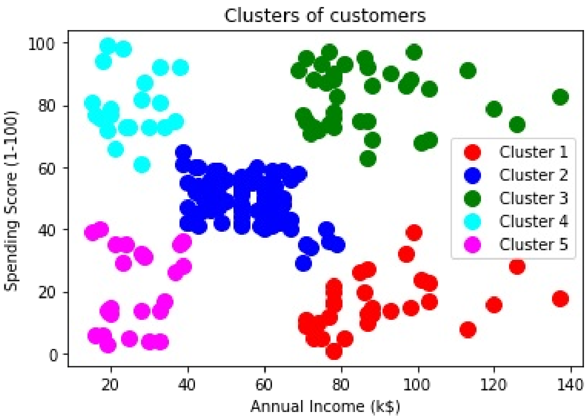
Training the Hierarchical Clustering model on the dataset

In [8]:
```
from sklearn.cluster import AgglomerativeClustering
hc = AgglomerativeClustering(n_clusters = 5, affinity = 'euclidean', linkage = 'ward')
y_hc = hc.fit_predict(X)
y_hc
```

Out[8]:
```
array([4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3,
       4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 1,
       4, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 2, 1, 2, 0, 2, 0, 2,
       1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 1, 2, 0, 2, 1, 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], dtype=int64)
```

Visualising the clusters

In [7]:
```
plt.scatter(X[y_hc == 0, 0], X[y_hc == 0, 1], s = 100, c = 'red', label = 'Cluster 1')
plt.scatter(X[y_hc == 1, 0], X[y_hc == 1, 1], s = 100, c = 'blue', label = 'Cluster 2')
plt.scatter(X[y_hc == 2, 0], X[y_hc == 2, 1], s = 100, c = 'green', label = 'Cluster 3')
plt.scatter(X[y_hc == 3, 0], X[y_hc == 3, 1], s = 100, c = 'cyan', label = 'Cluster 4')
plt.scatter(X[y_hc == 4, 0], X[y_hc == 4, 1], s = 100, c = 'magenta', label = 'Cluster 5')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



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Practical No - 7 : Artificial Neural Network

Importing the libraries

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

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
<ipython-input-1-af52a695d594> in <module>
      1 import numpy as np
      2 import pandas as pd
----> 3 import tensorflow as tf

ModuleNotFoundError: No module named 'tensorflow'
```

In [ ]:
```
tf.__version__
```

Part 1 - Data Preprocessing

Importing the dataset

In [4]:
```
dataset = pd.read_csv('Churn_Modelling.csv')
X = dataset.iloc[:, 3:-1].values
y = dataset.iloc[:, -1].values
```

In [5]:
```
print(X)
```

```
[[619 'France' 'Female' ... 1 1 101348.88]
 [608 'Spain' 'Female' ... 0 1 112542.58]
 [502 'France' 'Female' ... 1 0 113931.57]
 ...
 [709 'France' 'Female' ... 0 1 42085.58]
 [772 'Germany' 'Male' ... 1 0 92888.52]
 [792 'France' 'Female' ... 1 0 38190.78]]
```

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

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

Encoding categorical data

Label Encoding the "Gender" column

In [7]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
X[:, 2] = le.fit_transform(X[:, 2])
```

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

```
[[619 'France' 0 ... 1 1 101348.88]
 [608 'Spain' 0 ... 0 1 112542.58]
 [502 'France' 0 ... 1 0 113931.57]
 ...
 [709 'France' 0 ... 0 1 42085.58]
 [772 'Germany' 1 ... 1 0 92888.52]
 [792 'France' 0 ... 1 0 38190.78]]
```

One Hot Encoding the "Geography" column

In [9]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [1])], remainder='passthrough')
X = np.array(ct.fit_transform(X))
```

In [10]:
```python
print(X)
```

```
[[1.0 0.0 0.0 ... 1 1 101348.88]
 [0.0 0.0 1.0 ... 0 1 112542.58]
 [1.0 0.0 0.0 ... 1 0 113931.57]
 ...
 [1.0 0.0 0.0 ... 0 1 42085.58]
 [0.0 1.0 0.0 ... 1 0 92888.52]
 [1.0 0.0 0.0 ... 1 0 38190.78]]
```

Splitting the dataset into the Training set and Test set

In [11]:
```python
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
```

Feature Scaling

In [12]:
```python
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Part 2 - Building the ANN

Initializing the ANN

In [14]:
```python
ann = tf.keras.models.Sequential()
```

Adding the input layer and the first hidden layer

In [15]:
```python
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
```

Adding the second hidden layer

In [16]:
```python
ann.add(tf.keras.layers.Dense(units=6, activation='relu'))
```

Adding the output layer

In [17]:
```python
ann.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))
```

Part 3 - Training the ANN

Compiling the ANN

In [18]:
```python
ann.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
```

Training the ANN on the Training set

In [19]:
```python
ann.fit(X_train, y_train, batch_size = 32, epochs = 100)
```

```
Epoch 1/100
250/250 [==============================] - 2s 1ms/step - loss: 0.6397 - accuracy: 0.6693
Epoch 2/100
250/250 [==============================] - 0s 912us/step - loss: 0.4654 - accuracy: 0.8025
Epoch 3/100
250/250 [==============================] - 0s 882us/step - loss: 0.4239 - accuracy: 0.81760s - loss: 0.4200 - acc
uracy
Epoch 4/100
250/250 [==============================] - 0s 881us/step - loss: 0.4107 - accuracy: 0.8232
Epoch 5/100
250/250 [==============================] - 0s 879us/step - loss: 0.3861 - accuracy: 0.8381
Epoch 6/100
250/250 [==============================] - 0s 884us/step - loss: 0.3884 - accuracy: 0.8386
Epoch 7/100
250/250 [==============================] - 0s 874us/step - loss: 0.3714 - accuracy: 0.8424
Epoch 8/100
```

```
250/250 [==============================] - 0s 880us/step - loss: 0.3670 - accuracy: 0.8457
Epoch 9/100
250/250 [==============================] - 0s 918us/step - loss: 0.3653 - accuracy: 0.8469
Epoch 10/100
250/250 [==============================] - 0s 878us/step - loss: 0.3555 - accuracy: 0.8471
Epoch 11/100
250/250 [==============================] - 0s 897us/step - loss: 0.3470 - accuracy: 0.8579
Epoch 12/100
250/250 [==============================] - 0s 885us/step - loss: 0.3501 - accuracy: 0.8489
Epoch 13/100
250/250 [==============================] - 0s 907us/step - loss: 0.3507 - accuracy: 0.8535
Epoch 14/100
250/250 [==============================] - 0s 877us/step - loss: 0.3537 - accuracy: 0.8486
Epoch 15/100
250/250 [==============================] - 0s 875us/step - loss: 0.3524 - accuracy: 0.8527
Epoch 16/100
250/250 [==============================] - 0s 894us/step - loss: 0.3516 - accuracy: 0.8484
Epoch 17/100
250/250 [==============================] - 0s 1ms/step - loss: 0.3431 - accuracy: 0.8566
Epoch 18/100
250/250 [==============================] - 0s 912us/step - loss: 0.3620 - accuracy: 0.8471
Epoch 19/100
250/250 [==============================] - 0s 1ms/step - loss: 0.3472 - accuracy: 0.8582
Epoch 20/100
250/250 [==============================] - 0s 1ms/step - loss: 0.3383 - accuracy: 0.8621
Epoch 21/100
250/250 [==============================] - 0s 1ms/step - loss: 0.3505 - accuracy: 0.8476
Epoch 22/100
250/250 [==============================] - 0s 937us/step - loss: 0.3446 - accuracy: 0.8553
Epoch 23/100
250/250 [==============================] - 0s 873us/step - loss: 0.3311 - accuracy: 0.8665
Epoch 24/100
250/250 [==============================] - 0s 877us/step - loss: 0.3482 - accuracy: 0.8538
Epoch 25/100
250/250 [==============================] - 0s 879us/step - loss: 0.3520 - accuracy: 0.8522
Epoch 26/100
250/250 [==============================] - 0s 874us/step - loss: 0.3355 - accuracy: 0.8606
Epoch 27/100
250/250 [==============================] - 0s 879us/step - loss: 0.3549 - accuracy: 0.8545
Epoch 28/100
250/250 [==============================] - 0s 885us/step - loss: 0.3466 - accuracy: 0.8579
Epoch 29/100
250/250 [==============================] - 0s 865us/step - loss: 0.3389 - accuracy: 0.8573
Epoch 30/100
250/250 [==============================] - 0s 915us/step - loss: 0.3448 - accuracy: 0.8605
Epoch 31/100
250/250 [==============================] - 0s 891us/step - loss: 0.3361 - accuracy: 0.8656
Epoch 32/100
250/250 [==============================] - 0s 916us/step - loss: 0.3309 - accuracy: 0.8652
Epoch 33/100
250/250 [==============================] - 0s 944us/step - loss: 0.3356 - accuracy: 0.8649
Epoch 34/100
250/250 [==============================] - 0s 1ms/step - loss: 0.3360 - accuracy: 0.8626
Epoch 35/100
250/250 [==============================] - 0s 952us/step - loss: 0.3401 - accuracy: 0.8612
Epoch 36/100
250/250 [==============================] - 0s 1ms/step - loss: 0.3507 - accuracy: 0.8540
Epoch 37/100
250/250 [==============================] - 0s 937us/step - loss: 0.3255 - accuracy: 0.8695
Epoch 38/100
250/250 [==============================] - 0s 1ms/step - loss: 0.3375 - accuracy: 0.8602
Epoch 39/100
250/250 [==============================] - 0s 901us/step - loss: 0.3367 - accuracy: 0.8605
Epoch 40/100
250/250 [==============================] - 0s 905us/step - loss: 0.3371 - accuracy: 0.8642
Epoch 41/100
250/250 [==============================] - 0s 889us/step - loss: 0.3422 - accuracy: 0.8594
Epoch 42/100
250/250 [==============================] - 0s 913us/step - loss: 0.3416 - accuracy: 0.8603
Epoch 43/100
250/250 [==============================] - 0s 890us/step - loss: 0.3433 - accuracy: 0.8607
Epoch 44/100
250/250 [==============================] - 0s 888us/step - loss: 0.3356 - accuracy: 0.8613
Epoch 45/100
250/250 [==============================] - 0s 913us/step - loss: 0.3371 - accuracy: 0.86160s - loss: 0.3369 - acc
uracy: 0.86
Epoch 46/100
250/250 [==============================] - 0s 900us/step - loss: 0.3347 - accuracy: 0.8626
Epoch 47/100
250/250 [==============================] - 0s 927us/step - loss: 0.3395 - accuracy: 0.8608
Epoch 48/100
250/250 [==============================] - 0s 919us/step - loss: 0.3414 - accuracy: 0.8604
Epoch 49/100
```

```
250/250 [==============================] - 0s 891us/step - loss: 0.3339 - accuracy: 0.8659
Epoch 50/100
250/250 [==============================] - 0s 914us/step - loss: 0.3260 - accuracy: 0.8669
Epoch 51/100
250/250 [==============================] - 0s 911us/step - loss: 0.3423 - accuracy: 0.8556
Epoch 52/100
250/250 [==============================] - 0s 934us/step - loss: 0.3292 - accuracy: 0.8655
Epoch 53/100
250/250 [==============================] - 0s 922us/step - loss: 0.3340 - accuracy: 0.8657
Epoch 54/100
250/250 [==============================] - 0s 950us/step - loss: 0.3284 - accuracy: 0.8658
Epoch 55/100
250/250 [==============================] - 0s 878us/step - loss: 0.3281 - accuracy: 0.8677
Epoch 56/100
250/250 [==============================] - 0s 896us/step - loss: 0.3418 - accuracy: 0.8594
Epoch 57/100
250/250 [==============================] - 0s 873us/step - loss: 0.3415 - accuracy: 0.8557
Epoch 58/100
250/250 [==============================] - 0s 915us/step - loss: 0.3459 - accuracy: 0.8566
Epoch 59/100
250/250 [==============================] - 0s 952us/step - loss: 0.3465 - accuracy: 0.8571
Epoch 60/100
250/250 [==============================] - 0s 1ms/step - loss: 0.3359 - accuracy: 0.8627
Epoch 61/100
250/250 [==============================] - 0s 988us/step - loss: 0.3461 - accuracy: 0.8543
Epoch 62/100
250/250 [==============================] - 0s 944us/step - loss: 0.3426 - accuracy: 0.8594
Epoch 63/100
250/250 [==============================] - 0s 971us/step - loss: 0.3393 - accuracy: 0.8610
Epoch 64/100
250/250 [==============================] - 0s 914us/step - loss: 0.3376 - accuracy: 0.8646
Epoch 65/100
250/250 [==============================] - 0s 897us/step - loss: 0.3361 - accuracy: 0.8631
Epoch 66/100
250/250 [==============================] - 0s 990us/step - loss: 0.3341 - accuracy: 0.8630
Epoch 67/100
250/250 [==============================] - 0s 890us/step - loss: 0.3462 - accuracy: 0.8588
Epoch 68/100
250/250 [==============================] - 0s 885us/step - loss: 0.3418 - accuracy: 0.8607
Epoch 69/100
250/250 [==============================] - 0s 893us/step - loss: 0.3328 - accuracy: 0.8654
Epoch 70/100
250/250 [==============================] - 0s 914us/step - loss: 0.3402 - accuracy: 0.8604
Epoch 71/100
250/250 [==============================] - 0s 877us/step - loss: 0.3358 - accuracy: 0.8611
Epoch 72/100
250/250 [==============================] - 0s 881us/step - loss: 0.3354 - accuracy: 0.8670
Epoch 73/100
250/250 [==============================] - 0s 884us/step - loss: 0.3357 - accuracy: 0.8657
Epoch 74/100
250/250 [==============================] - 0s 879us/step - loss: 0.3379 - accuracy: 0.8582
Epoch 75/100
250/250 [==============================] - 0s 882us/step - loss: 0.3417 - accuracy: 0.8614
Epoch 76/100
250/250 [==============================] - 0s 884us/step - loss: 0.3391 - accuracy: 0.8603
Epoch 77/100
250/250 [==============================] - 0s 870us/step - loss: 0.3232 - accuracy: 0.8676
Epoch 78/100
250/250 [==============================] - 0s 906us/step - loss: 0.3466 - accuracy: 0.8572
Epoch 79/100
250/250 [==============================] - 0s 892us/step - loss: 0.3240 - accuracy: 0.8688
Epoch 80/100
250/250 [==============================] - 0s 970us/step - loss: 0.3336 - accuracy: 0.86390s - loss: 0.3316 - acc
uracy: 0.
Epoch 81/100
250/250 [==============================] - 0s 978us/step - loss: 0.3364 - accuracy: 0.8624
Epoch 82/100
250/250 [==============================] - 0s 1ms/step - loss: 0.3345 - accuracy: 0.8613
Epoch 83/100
250/250 [==============================] - 0s 980us/step - loss: 0.3409 - accuracy: 0.8658
Epoch 84/100
250/250 [==============================] - 0s 955us/step - loss: 0.3331 - accuracy: 0.8632
Epoch 85/100
250/250 [==============================] - 0s 911us/step - loss: 0.3382 - accuracy: 0.8617
Epoch 86/100
250/250 [==============================] - 0s 979us/step - loss: 0.3430 - accuracy: 0.8610
Epoch 87/100
250/250 [==============================] - 0s 867us/step - loss: 0.3294 - accuracy: 0.8677
Epoch 88/100
250/250 [==============================] - 0s 1ms/step - loss: 0.3357 - accuracy: 0.8616
Epoch 89/100
250/250 [==============================] - 0s 1ms/step - loss: 0.3396 - accuracy: 0.8610
Epoch 90/100
```

```
250/250 [==============================] - 0s 1ms/step - loss: 0.3355 - accuracy: 0.8632
Epoch 91/100
250/250 [==============================] - 0s 933us/step - loss: 0.3393 - accuracy: 0.85940s - loss: 0.3427 - acc
uracy: 0.
Epoch 92/100
250/250 [==============================] - 0s 890us/step - loss: 0.3302 - accuracy: 0.8617
Epoch 93/100
250/250 [==============================] - 0s 887us/step - loss: 0.3357 - accuracy: 0.8658
Epoch 94/100
250/250 [==============================] - 0s 897us/step - loss: 0.3361 - accuracy: 0.8614
Epoch 95/100
250/250 [==============================] - 0s 900us/step - loss: 0.3347 - accuracy: 0.8608
Epoch 96/100
250/250 [==============================] - 0s 903us/step - loss: 0.3383 - accuracy: 0.8613
Epoch 97/100
250/250 [==============================] - 0s 930us/step - loss: 0.3404 - accuracy: 0.8599
Epoch 98/100
250/250 [==============================] - 0s 1ms/step - loss: 0.3367 - accuracy: 0.8600
Epoch 99/100
250/250 [==============================] - 0s 1ms/step - loss: 0.3524 - accuracy: 0.8534
Epoch 100/100
250/250 [==============================] - 0s 860us/step - loss: 0.3318 - accuracy: 0.8678
```

Out[19]:
```
<tensorflow.python.keras.callbacks.History at 0x1f147dd0948>
```

Part 4 - Making the predictions and evaluating the model

Predicting the result of a single observation

Homework

Use our ANN model to predict if the customer with the following informations will leave the bank:

Geography: France

Credit Score: 600

Gender: Male

Age: 40 years old

Tenure: 3 years

Balance: $ 60000

Number of Products: 2

Does this customer have a credit card ? Yes

Is this customer an Active Member: Yes

Estimated Salary: $ 50000

So, should we say goodbye to that customer ?

Solution

In [20]:
```python
print(ann.predict(sc.transform([[1, 0, 0, 600, 1, 40, 3, 60000, 2, 1, 1, 50000]])) > 0.5)
```

```
[[False]]
```

Therefore, our ANN model predicts that this customer stays in the bank!

Important note 1: Notice that the values of the features were all input in a double pair of square brackets. That's because the "predict" method always expects a 2D array as the format of its inputs. And putting our values into a double pair of square brackets makes the input exactly a 2D array.

Important note 2: Notice also that the "France" country was not input as a string in the last column but as "1, 0, 0" in the first three columns. That's because of course the predict method expects the one-hot-encoded values of the state, and as we see in the first row of the matrix of features X, "France" was encoded as "1, 0, 0". And be careful to include these values in the first three columns, because the dummy variables are always created in the first columns.

Predicting the Test set results

In [21]:
```
y_pred = ann.predict(X_test)
y_pred = (y_pred > 0.5)
print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
```

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

Making the Confusion Matrix

In [20]:
```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[1516   79]
 [ 200  205]]
```

Out[20]:
```
0.8605
```

Practical No - 8 : Convolutional Neural Network

Importing the libraries

In [1]:
```
import tensorflow as tf
from keras.preprocessing.image import ImageDataGenerator
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
<ipython-input-1-69667bf45035> in <module>()
      1 import tensorflow as tf
----> 2 from keras.preprocessing.image import ImageDataGenerator

ModuleNotFoundError: No module named 'keras'
```

In [0]:
```
tf.__version__
```

Part 1 - Data Preprocessing

Preprocessing the Training set

In [0]:
```
train_datagen = ImageDataGenerator(rescale = 1./255,
                                   shear_range = 0.2,
                                   zoom_range = 0.2,
                                   horizontal_flip = True)
training_set = train_datagen.flow_from_directory('dataset/training_set',
                                                 target_size = (64, 64),
                                                 batch_size = 32,
                                                 class_mode = 'binary')
```

Preprocessing the Test set

In [0]:
```
test_datagen = ImageDataGenerator(rescale = 1./255)
test_set = test_datagen.flow_from_directory('dataset/test_set',
                                            target_size = (64, 64),
                                            batch_size = 32,
                                            class_mode = 'binary')
```

Part 2 - Building the CNN

Initialising the CNN

In [0]:
```
cnn = tf.keras.models.Sequential()
```

Step 1 - Convolution

In [0]:
```
cnn.add(tf.keras.layers.Conv2D(filters=32, kernel_size=3, activation='relu', input_shape=[64, 64, 3]))
```

Step 2 - Pooling

In [0]:
```
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))
```

Adding a second convolutional layer

In [0]:
```
cnn.add(tf.keras.layers.Conv2D(filters=32, kernel_size=3, activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))
```

Step 3 - Flattening

In [0]:
```
cnn.add(tf.keras.layers.Flatten())
```

Step 4 - Full Connection

In [0]:
```
cnn.add(tf.keras.layers.Dense(units=128, activation='relu'))
```

Step 5 - Output Layer

In [0]:
```
cnn.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))
```

Part 3 - Training the CNN

Compiling the CNN

In [0]:
```
cnn.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
```

Training the CNN on the Training set and evaluating it on the Test set

In [0]:
```
cnn.fit(x = training_set, validation_data = test_set, epochs = 25)
```

Part 4 - Making a single prediction

In [0]:
```
import numpy as np
from keras.preprocessing import image
test_image = image.load_img('dataset/single_prediction/cat_or_dog_1.jpg', target_size = (64, 64))
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis = 0)
result = cnn.predict(test_image)
training_set.class_indices
if result[0][0] == 1:
  prediction = 'dog'
else:
  prediction = 'cat'
```

In [0]:
```
print(prediction)
```