ROLL NO: 31440

DSBDAL Assignment No - 5

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
df=pd.read_csv("Social_Network_Ads.csv")
```

In [3]:

```
df.head()
```

Out[3]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0

In [4]:

```
df.info
```

Out[4]:

```
<bound method DataFrame.info of      User ID  Gender  Age  EstimatedSalary
Purchased
0    15624510    Male   19            19000          0
1    15810944    Male   35            20000          0
2    15668575  Female   26            43000          0
3    15603246  Female   27            57000          0
4    15804002    Male   19            76000          0
..        ...     ...  ...              ...        ...
395  15691863  Female   46            41000          1
396  15706071    Male   51            23000          1
397  15654296  Female   50            20000          1
398  15755018    Male   36            33000          0
399  15594041  Female   49            36000          1

[400 rows x 5 columns]>
```

In [5]:

```
df.dtypes
```

Out[5]:

```
User ID              int64
Gender              object
Age                  int64
EstimatedSalary      int64
Purchased            int64
dtype: object
```

In [6]:

```
df.Purchased.value_counts()
```

Out[6]:

```
0    257
1    143
Name: Purchased, dtype: int64
```

In [7]:

```
data=df.iloc[:,1:]
data
```

Out[7]:

	Gender	Age	EstimatedSalary	Purchased
0	Male	19	19000	0
1	Male	35	20000	0
2	Female	26	43000	0
3	Female	27	57000	0
4	Male	19	76000	0
...	...	...	...	...
395	Female	46	41000	1
396	Male	51	23000	1
397	Female	50	20000	1
398	Male	36	33000	0
399	Female	49	36000	1

400 rows × 4 columns

In [8]:

```
data['Gender'].unique()
```

Out[8]:

```
array(['Male', 'Female'], dtype=object)
```

In [9]:

```
data['Gender']=data['Gender'].map({'Male':0,'Female':1})
data.head()
```

Out[9]:

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

In [ ]:

```

```

In [10]:

```
data.describe()
```

Out[10]:

	Gender	Age	EstimatedSalary	Purchased
count	400.000000	400.000000	400.000000	400.000000
mean	0.510000	37.655000	69742.500000	0.357500
std	0.500526	10.482877	34096.960282	0.479864
min	0.000000	18.000000	15000.000000	0.000000
25%	0.000000	29.750000	43000.000000	0.000000
50%	1.000000	37.000000	70000.000000	0.000000
75%	1.000000	46.000000	88000.000000	1.000000
max	1.000000	60.000000	150000.000000	1.000000

In [11]:

```
data.isnull().sum()
```

Out[11]:

```
Gender             0
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64
```

In [12]:

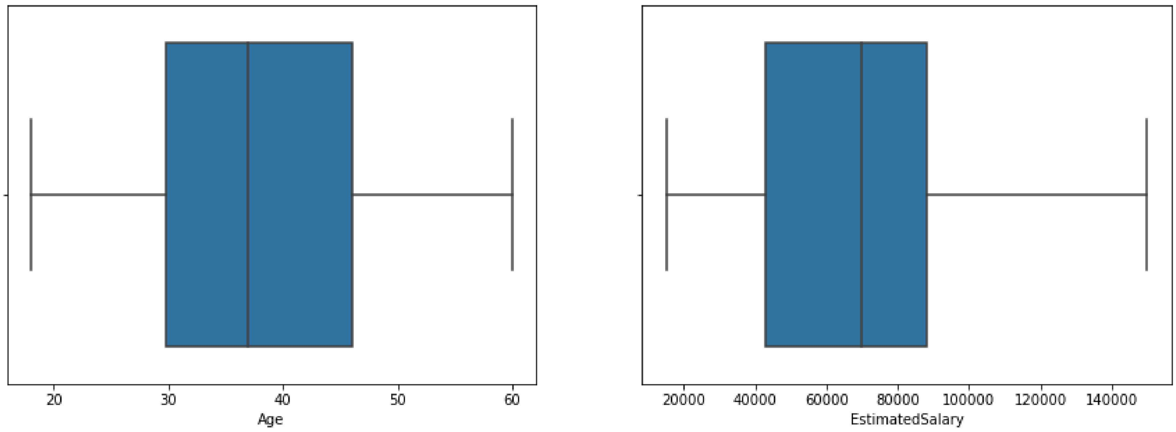
```
cols=['Age', 'EstimatedSalary']
cols
```

Out[12]:

```
['Age', 'EstimatedSalary']
```

In [13]:

```
t=1
plt.figure(figsize=(15,5))
for i in cols:
    plt.subplot(1,2,t)
    t=t+1
    sns.boxplot(data[i])
```



In [14]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

scaler.fit(data[['Age','EstimatedSalary']])
data[['Age','EstimatedSalary']] = scaler.transform(df[['Age','EstimatedSalary']])
```

In [15]:

```
X=data[['Age','EstimatedSalary']]
y=data[['Purchased']]
```

In [16]:

```
X
```

Out[16]:

	Age	EstimatedSalary
0	0.023810	0.029630
1	0.404762	0.037037
2	0.190476	0.207407
3	0.214286	0.311111
4	0.023810	0.451852
...	...	...
395	0.666667	0.192593
396	0.785714	0.059259
397	0.761905	0.037037
398	0.428571	0.133333
399	0.738095	0.155556

400 rows × 2 columns

In [17]:

```
y
```

Out[17]:

	Purchased
0	0
1	0
2	0
3	0
4	0
...	...
395	1
396	1
397	1
398	0
399	1

400 rows × 1 columns

In [18]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 0
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(280, 2)
(120, 2)
(280, 1)
(120, 1)
```

In [ ]:

```

```

In [19]:

```
from sklearn.linear_model import LogisticRegression
log_model=LogisticRegression()
log_model.fit(X_train,y_train)

y_pred=log_model.predict(X_test)
```

In [20]:

```
accuracy=log_model.score(X_test,y_test)
```

In [21]:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
tp=cm[0][0]
fp=cm[0][1]
fn=cm[1][0]
tn=cm[1][1]
print("Confusion Matrix")
print("TP: ",tp,"\tFP: ",fp)
print("FN: ",fn,"\tTN: ",tn)
```

```
Confusion Matrix
TP:  76         FP:  3
FN:  16         TN:  25
```

Accuracy

Accuracy (ACC) is calculated as the number of all correct predictions divided by the total number of the dataset. The best accuracy is 1.0, whereas the worst is 0.0.
Accuracy=(TP+TN)/(TP+TN+FP+FN)

Error Rate

Error rate (ERR) is calculated as the number of all incorrect predictions divided by the total number of the dataset. The best error rate is 0.0, whereas the worst is 1.0.It can also be calculated by 1 – Accuracy
Error rate=(FP+FN)/(TP+TN+FP+FN)

Precision
Precision (PREC) is calculated as the number of correct positive predictions divided by the total number of positive predictions. It is also called positive predictive value (PPV). The best precision is 1.0, whereas the worst is 0.0.
Precision=TP/TP+FP

Recall
Recall (REC) is calculated as the number of correct positive predictions divided by the total number of positives. It is also called Sensitivity (SN) or true positive rate (TPR). The best Recall is 1.0, whereas the worst is 0.0.
Recall=TP/TP+FN

In [22]:

```
errorRate=1-accuracy
precision = tp/(tp+fp)
recall=tp/(tp+fn)

print('Accuracy:',round(accuracy,2))
print('Error Rate:',round(errorRate,2))
print('Precision:',round(precision,2))
print('Recall: ',round(recall,2))
```

```
Accuracy: 0.84
Error Rate: 0.16
Precision: 0.96
Recall:  0.83
```

In [23]:

```
a=(tp+tn)/(tp+tn+fn+fp)
a
```

Out[23]:

```
0.8416666666666667
```

In [ ]:

```

```