```
In [ ]: """
Data Analytics II

1. Implement logistic regression using Python/R to perform classification on
Social_Network_Ads.csv dataset.

2. Compute Confusion matrix to find TP, FP, TN, FN, Accuracy, Error rate, Precision, Recall
on the given dataset.

In [10]: # Importing the dependencies
    import pandas as pd
    import numpy as np
    import seaborn as sns
    import matplotlib.pyplot as plt

In [2]: # Importing dataset from local file
    df = pd.read_csv("Social_Network_Ads.csv")
```

[n	[3]	df
	r 2 1	u i

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
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 × 5 columns

In [4]: df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 400 entries, 0 to 399
Data columns (total 5 columns):

Jata	columns (total 5	columns):	
#	Column	Non-Null Count	Dtype
0	User ID	400 non-null	int64
1	Gender	400 non-null	object
2	Age	400 non-null	int64
3	EstimatedSalary	400 non-null	int64
4	Purchased	400 non-null	int64

dtypes: int64(4), object(1)

memory usage: 15.8+ KB

```
In [5]: df.isnull().sum()
          # no null values;
 Out[5]: User ID
                                 0
          Gender
          Age
          EstimatedSalary
          Purchased
          dtype: int64
 In [6]: df.shape
 Out[6]: (400, 5)
 In [9]: df.describe()
 Out[9]:
                      User ID
                                    Age EstimatedSalary Purchased
           count 4.000000e+02 400.000000
                                             400.000000 400.000000
            mean 1.569154e+07
                               37.655000
                                           69742.500000
                                                         0.357500
             std 7.165832e+04
                               10.482877
                                           34096.960282
                                                         0.479864
             min 1.556669e+07
                               18.000000
                                           15000.000000
                                                         0.000000
            25% 1.562676e+07
                                           43000.000000
                               29.750000
                                                         0.000000
             50% 1.569434e+07
                               37.000000
                                           70000.000000
                                                         0.000000
            75% 1.575036e+07
                               46.000000
                                           88000.000000
                                                         1.000000
            max 1.581524e+07
                               60.000000
                                          150000.000000
                                                         1.000000
In [12]: X = df.iloc[:, [2, 3]].values
          # X = df[['EstimatedSalary', 'Age']]
          y = df.iloc[:, 4].values
          # y = df['Purchased']
```

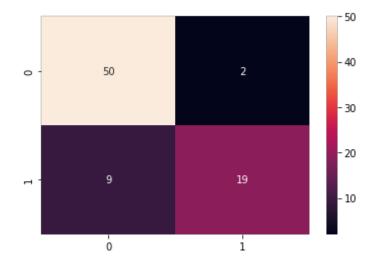
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Test-size = 0.2

```
In [63]: # Splitting the dataset into the Training set and Test set
         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 = 42)
In [64]: # Feature Scaling
         from sklearn.preprocessing import StandardScaler
         sc = StandardScaler()
         X train = sc.fit transform(X train)
         X test = sc.transform(X test)
In [65]: from sklearn.linear model import LogisticRegression
         lr = LogisticRegression(random state = 42)
         lr.fit(X train, y train)
Out[65]:
                  LogisticRegression
         LogisticRegression(random state=42)
In [66]: y pred = lr.predict(X test)
In [67]: y pred
Out[67]: array([0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0,
                0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0,
                1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0])
In [68]: y test
Out[68]: array([0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0,
                1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1,
                0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1,
                1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1])
```

```
In [69]: from sklearn.metrics import confusion matrix
         cm = confusion_matrix(y_test, y_pred)
         print(cm)
         # TP FP
         # FN TN
         [[50 2]
          [ 9 19]]
In [70]: sns.heatmap(cm ,annot=True)
```

Out[70]: <AxesSubplot: >



```
In [71]: from sklearn.metrics import classification report
         print(classification report(y test,y pred))
                       precision
                                     recall f1-score
                                                        support
                    0
                            0.85
                                       0.96
                                                 0.90
                                                             52
                            0.90
                                       0.68
                                                 0.78
                                                             28
                    1
                                                 0.86
                                                             80
             accuracy
                                       0.82
                                                 0.84
                                                             80
            macro avg
                            0.88
         weighted avg
                            0.87
                                       0.86
                                                 0.86
                                                             80
In [72]: from sklearn.metrics import accuracy score
         accuracy = accuracy score(y test, y pred)
         accuracy
Out[72]: 0.8625
In [73]: error rate = 1-accuracy
         error rate
Out[73]: 0.1374999999999996
```

Test-size = 0.25

```
In [39]: X train, X test, y train, y test = train test split(X, y, test size=0.25, random state=25)
```

```
In [40]: X train = sc.fit transform(X train)
         X test = sc.transform(X test)
```

Test-size = 0.3

accuracy

```
In [52]: X train, X test, y train, y test = train test split(X, y, test size=0.3, random state=25)
In [53]: X train = sc.fit transform(X train)
         X test = sc.transform(X test)
In [54]: | lr = LogisticRegression(random state=30)
         lr.fit(X train, y train)
Out[54]:
                   LogisticRegression
         LogisticRegression(random state=30)
In [55]: y pred = lr.predict(X test)
In [56]: cm = confusion matrix(y test, y pred)
In [57]: print(cm)
         # TP FP
         # FN TN
         [[70 7]
          [16 27]]
In [58]: print(classification report(y test, y pred))
                       precision
                                     recall f1-score
                                                        support
                                       0.91
                                                 0.86
                     0
                             0.81
                                                             77
                                       0.63
                    1
                             0.79
                                                 0.70
                                                             43
                                                             120
                                                 0.81
             accuracy
                                       0.77
                                                 0.78
                                                             120
            macro avg
                             0.80
         weighted avg
                             0.81
                                       0.81
                                                 0.80
                                                             120
```