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Assignment No : 05
Data Analytics II

1. Implement logistic regression using Pyt

hon/R to perform classification on

Social_Network_Ads.csv dataset.

2. Compute Confusion matrix to find TP, F

P, TN, FN, Accuracy, Error rate, Precision, Recall on the given dataset.

STEP 1

INCLUDE NECESSORY LIBRARIES

In [3]: import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

STEP 2

upload dataset

In [5]: data=pd.read_csv("C:\\Users\\alisu\\Downloads\\Social_Network_Ads.csv")

In [6]: data

Out[6]:

User ID	Gender	Age	EstimatedSalary	Purchased
15624510	Male	19	19000	0
15810944	Male	35	20000	0
15668575	Female	26	43000	0
15603246	Female	27	57000	0
15804002	Male	19	76000	0
15691863	Female	46	41000	1
15706071	Male	51	23000	1
15654296	Female	50	20000	1
15755018	Male	36	33000	0
15594041	Female	49	36000	1
	15624510 15810944 15668575 15603246 15804002 15691863 15706071 15654296 15755018	15624510 Male 15810944 Male 15668575 Female 15603246 Female 15804002 Male 15691863 Female 15706071 Male 15654296 Female 15755018 Male	15624510 Male 19 15810944 Male 35 15668575 Female 26 15603246 Female 27 15804002 Male 19 15691863 Female 46 15706071 Male 51 15654296 Female 50 15755018 Male 36	15810944 Male 35 20000 15668575 Female 26 43000 15603246 Female 27 57000 15804002 Male 19 76000 15691863 Female 46 41000 15706071 Male 51 23000 15654296 Female 50 20000 15755018 Male 36 33000

400 rows × 5 columns

STEP 3

EXPLORATORY DATA ANALYSIS

```
In [8]: data.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data 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 [9]: data.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	29.750000	43000.000000	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 [10]: data.isnull().sum()

Out[10]: User ID 0
Gender 0

Age 0
EstimatedSalary 0
Purchased 0

dtype: int64

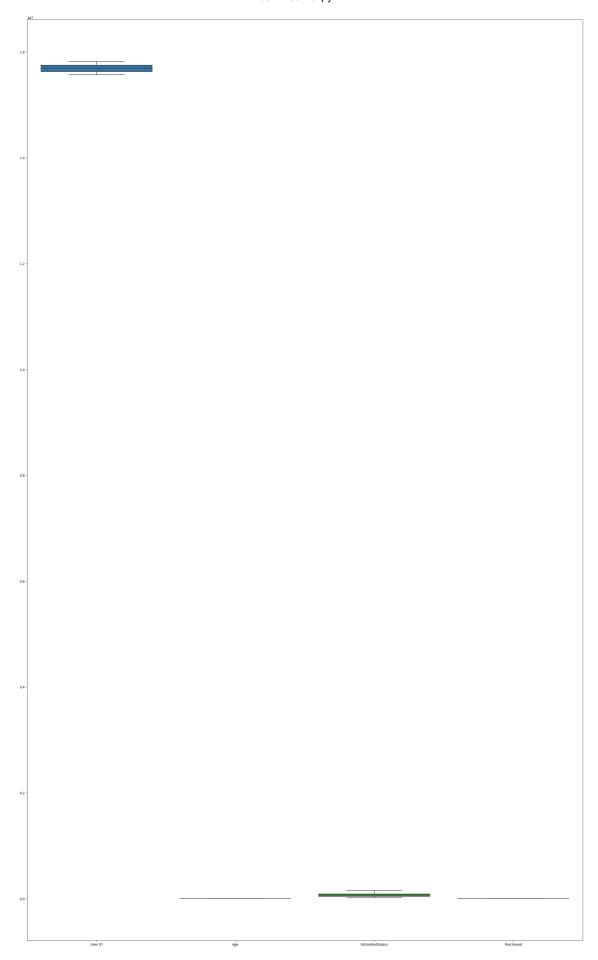
```
In [11]:
         data.duplicated()
Out[11]: 0
                 False
          1
                 False
          2
                 False
          3
                 False
          4
                 False
                 . . .
          395
                 False
          396
                 False
                 False
          397
                 False
          398
          399
                 False
          Length: 400, dtype: bool
```

STEP 4

To find outliers

```
In [13]: plt.figure(figsize=(30,50))
sns.boxplot(data)
```

Out[13]: <Axes: >



STEP 5

Conversion of categorical variable to numerical variable

In [14]: data.Gender=data.Gender.replace({"Male":1,"Female":0})

In [15]: data

Out[15]:

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

400 rows × 5 columns

Step 6

Splitting dependent and independent variables

```
In [16]: x=data.drop( "Purchased",axis="columns")
```

In [17]: x

Out[17]:

	User ID	Gender	Age	EstimatedSalary
0	15624510	1	19	19000
1	15810944	1	35	20000
2	15668575	0	26	43000
3	15603246	0	27	57000
4	15804002	1	19	76000
395	15691863	0	46	41000
396	15706071	1	51	23000
397	15654296	0	50	20000
398	15755018	1	36	33000
399	15594041	0	49	36000

400 rows × 4 columns

```
In [18]: y=data.Purchased
```

```
In [19]: y
```

```
Out[19]: 0 0
1 0
```

2 0 3 0 4 0

399 1

Name: Purchased, Length: 400, dtype: int64

STEP 7

Split the dataset

```
In [20]: from sklearn.model_selection import train_test_split
    xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.2,random_state=3)
```

In [21]: xtrain

Out[21]:

	User ID	Gender	Age	EstimatedSalary
239	15772073	0	53	143000
188	15674206	1	35	72000
240	15701537	1	42	149000
23	15599081	0	45	22000
343	15629739	0	47	51000
256	15609637	0	41	72000
131	15801247	1	33	31000
249	15753102	0	35	97000
152	15699247	1	31	76000
362	15768072	0	47	50000

320 rows × 4 columns

```
In [22]: ytrain
```

Out[22]: 239

Name: Purchased, Length: 320, dtype: int64

In [23]: xtest

Out[23]:

	User ID	Gender	Age	EstimatedSalary
376	15596984	0	46	74000
16	15733883	1	47	25000
365	15807525	0	59	29000
82	15709476	1	20	49000
107	15789863	1	27	89000
246	15638003	0	35	50000
10	15570769	0	26	80000
115	15689237	1	40	57000
74	15592877	1	32	18000
194	15689751	1	28	89000

80 rows × 4 columns

```
In [24]:
         ytest
Out[24]: 376
                 0
          16
                 1
          365
                 1
          82
                 0
          107
                 0
          246
                 0
          10
                 0
          115
                 0
          74
                 0
          194
          Name: Purchased, Length: 80, dtype: int64
```

STEP 8

Use of logistic regression

LogisticRegression()

```
In [25]: from sklearn.linear_model import LogisticRegression
    model=LogisticRegression()

In [26]: model

Out[26]: v LogisticRegression
```

In [31]: compare_result.head(50)

Out[31]:

٦.,	1			
٦u	rcl	Пa	se	u

- 0
- 0
- 0
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- 0 0
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- 0 0
- 0
- 1
- 0
- 0 0
- 1
- 0 10 0
- 0
- 1

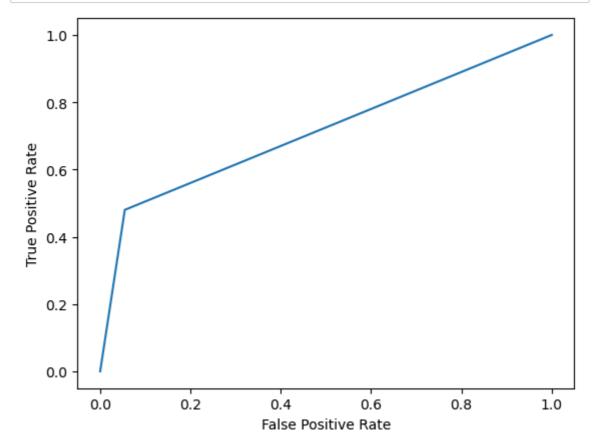
0

010

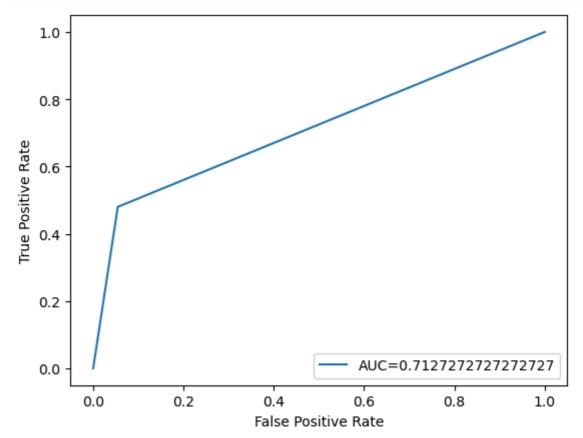
Purchased

```
0 0
                 1 1
                 1 1
                 1 1
                 0 0
                 1 0
                 0 0
                 0 0
                 1 1
                 0 0
                 0 0
In [46]: from sklearn.metrics import confusion_matrix , classification_report ,preci
         from sklearn.metrics import accuracy_score ,roc_curve , erroer_rate
In [38]: | accuracy=accuracy_score(ytest,y_predict)
In [39]: accuracy
Out[39]: 0.8
In [40]: |confusion_matrix(ytest,y_predict)
Out[40]: array([[52, 3],
                [13, 12]], dtype=int64)
In [42]: precision_score(ytest,y_predict)
Out[42]: 0.8
In [43]: |f1_score(ytest,y_predict)
Out[43]: 0.6
In [44]: roc_auc_score(ytest,y_predict)
Out[44]: 0.7127272727272727
```

```
In [47]: fpr, tpr, _ = roc_curve(ytest, y_predict)
#create ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



```
In [48]: auc= roc_auc_score(ytest,y_predict)
    plt.plot(fpr,tpr,label="AUC="+str(auc))
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.legend(loc=4)
    plt.show()
```



```
In [52]: cr= classification_report(ytest,y_predict)
print(cr)
```

	precision	recall	f1-score	support
0	0.80	0.95	0.87	55
1	0.80	0.48	0.60	25
accuracy			0.80	80
macro avg	0.80	0.71	0.73	80
weighted avg	0.80	0.80	0.78	80

```
In [55]: y_predict= model.predict(xtest)
print("Testing accuracy:", model.score(xtest,ytest)*100)
```

Testing accuracy: 80.0