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Practical No:- 5

1. Implement logistic regression using Python/R to perform classification on Social_Network_Ads.csv dataset. Compute Confusion matrix to find TP, FP, TN, FN, Accuracy, Error rate, Precision, Recall on the given dataset

Import all the required Python Libraries.

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

```
In [2]: df = pd.read_csv('Social_Network_Ads.csv')
In [3]: df.head()
```

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

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()
```

```
<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 [5]: df.describe()
```

Out[5]:

	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 [6]: X = df[['Age', 'EstimatedSalary']]
        Y = df['Purchased']
```

In [7]:
```
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
print(f'Train Dataset Size - X: {X_train.shape}, Y: {Y_train.shape}') print(f'Test Dataset
Size - X: {X_test.shape}, Y: {Y_test.shape}')
```

```
Train Dataset Size - X: (300, 2), Y: (300,)
Test Dataset Size - X: (100, 2), Y: (100,)
```

In [8]:
```
import matplotlib.pyplot as plt import seaborn as sns from
 sklearn.linear_model import LogisticRegression lm =
 LogisticRegression(random_state = 0, solver='lbfgs' )
 lm.fit(X_train, Y_train) predictions = lm.predict(X_test)
```

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

Confusion matrix

In [9]:
```
from sklearn.metrics import classification_report cm
 = classification_report(Y_test, predictions)
 print('Classification report : \n', cm)
```

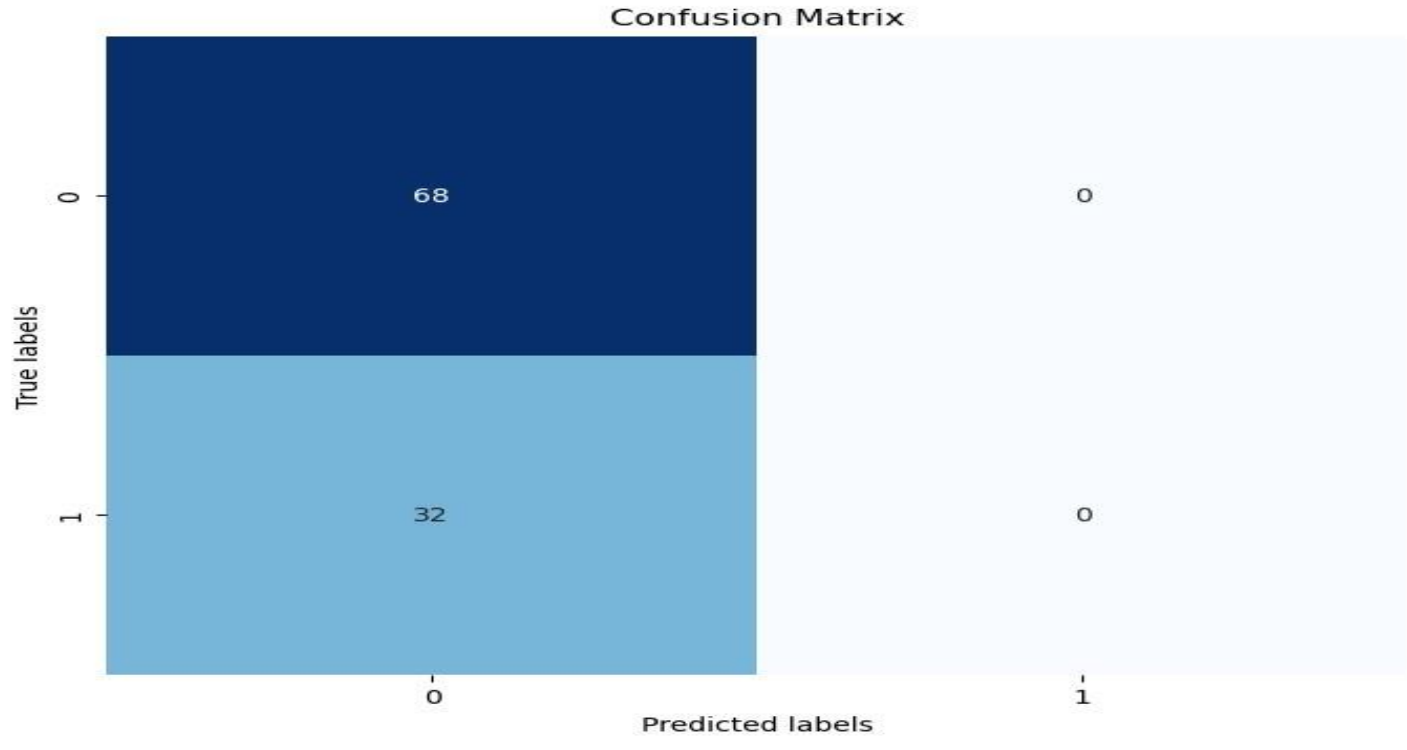
```
Classification report :

              precision    recall  f1-score   support

           0       0.68      1.00      0.81        68
           1       0.00      0.00      0.00        32

accuracy                           0.68       100
macro avg          0.34      0.50      0.40       100
weighted avg       0.46      0.68      0.55       100
```

In [10]:
```
from sklearn.metrics import classification_report, confusion_matrix
conf_matrix = confusion_matrix(Y_test, predictions)
plt.figure(figsize=(8, 6)) sns.heatmap(conf_matrix, annot=True, fmt='d',
cmap='Blues', cbar=False) plt.xlabel('Predicted labels')
plt.ylabel('True labels') plt.title('Confusion Matrix') plt.show()
```



In [12]:

```
y_pred =
lm.predict(X_test) cm =
confusion_matrix(Y_test,
y_pred)
TN = cm[0, 0]
FP = cm[0, 1]
FN = cm[1, 0] TP = cm[1, 1] accuracy
= (TP + TN) / float(TP + TN + FP +
FN) error_rate = (FP + FN) / float(TP
+ TN + FP + FN) precision = TP /
float(TP + FP) recall = TP / float(TP
+ FN) print("\nPerformance Metrics:")
print("True Positives (TP):", TP)
print("False Positives (FP):", FP)
print("True Negatives (TN):", TN)
print("False Negatives (FN):", FN)
print("Accuracy:", accuracy)
print("Error Rate:", error_rate)
print("Precision:", precision)
print("Recall:", recall)
```

```
Performance Metrics:
True Positives (TP): 0
False Positives (FP): 0
True Negatives (TN): 68
False Negatives (FN): 32
Accuracy: 0.68
Error Rate: 0.32
Precision: nan
Recall: 0.0
```