

practical-05

April 26, 2024

```
[30]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

```
[9]: data = pd.read_csv("C:/Users/gugal/Desktop/THIRD 2/PRACTICALS/DS/CODES/DATASETS/
↳Social_Network_ads.csv")
data
```

```
[9]:
```

	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]

```
[10]: data.isnull().sum()
```

```
[10]: User ID      0
Gender        0
Age           0
EstimatedSalary  0
Purchased     0
dtype: int64
```

```
[11]: 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
```

```
[5]: data.columns
```

```
[5]: Index(['User ID', 'Gender', 'Age', 'EstimatedSalary', 'Purchased'],
dtype='object')
```

```
[6]: data.describe()
```

```
[6]:
```

	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

```
[17]: le = LabelEncoder()
data['Gender'] = le.fit_transform(data['Gender'])
data['Gender'].unique()
```

```
[17]: array([1, 0], dtype=int64)
```

```
[18]: data
```

```
[18]:
```

	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 x 5 columns]

```
[19]: X = data[['User ID', 'Gender', 'Age', 'EstimatedSalary']].values
X
```

```
[19]: array([[15624510,      1,      19,    19000],
             [15810944,      1,      35,    20000],
             [15668575,      0,      26,    43000],
             ...,
             [15654296,      0,      50,    20000],
             [15755018,      1,      36,    33000],
             [15594041,      0,      49,    36000]], dtype=int64)
```

```
[20]: Y = data['Purchased'].values
Y
```

```
[20]: array([0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1,
             1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
             0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
             0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
             0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
             0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
             0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
             0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
             0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
             0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1,
             0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0,
             1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0,
             1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1,
             0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1,
             1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1,
             0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0,
             1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1,
             0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1,
             1, 1, 0, 1], dtype=int64)
```

```
[22]: X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.25,
↪random_state=0)
```

```
[23]: print(len(Y_test))
```

100

```
[25]: model = LogisticRegression()  
      model.fit(X_train,Y_train)
```

```
[25]: LogisticRegression()
```

```
[46]: prediction = model.predict(X_test)  
      print('Accuracy is', metrics.accuracy_score(Y_test,prediction))
```

Accuracy is 0.89

```
[28]: prediction
```

```
[28]: array([0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1,  
          0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,  
          1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,  
          0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1,  
          0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1], dtype=int64)
```

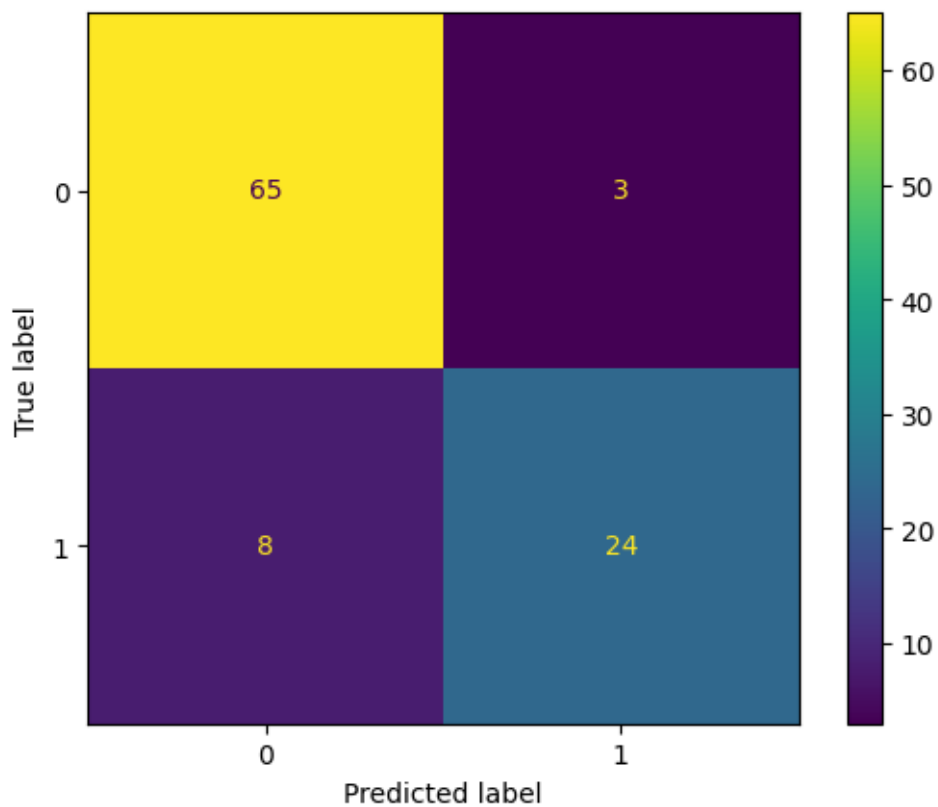
```
[29]: print(len(prediction))
```

100

```
[31]: CM = confusion_matrix(Y_test,prediction)  
      CM
```

```
[31]: array([[65,  3],  
          [ 8, 24]], dtype=int64)
```

```
[34]: disp = ConfusionMatrixDisplay(confusion_matrix=CM)  
      disp.plot()  
      plt.show()
```



```
[35]: TN = CM[0, 0]
      FP = CM[0, 1]
      FN = CM[1, 0]
      TP = CM[1, 1]

      print("True Negative (TN):", TN)
      print("False Positive (FP):", FP)
      print("False Negative (FN):", FN)
      print("True Positive (TP):", TP)
```

```
True Negative (TN): 65
False Positive (FP): 3
False Negative (FN): 8
True Positive (TP): 24
```

```
[37]: acc= (TP + TN)/(TP+FP+TN+FN)
      acc
```

```
[37]: 0.89
```

```
[38]: # Error Rate
Error_Rate = (FP + FN)/(TP+FP+TN+FN)
Error_Rate
```

[38]: 0.11

```
[48]: # Precision
Precision = (TP)/(TP+FP)
Precision
```

[48]: 0.8888888888888888

```
[49]: # Recall
Recall = (TP)/(TP+FN)
Recall
```

[49]: 0.75