2.Logistic Regression - Binary Class-Exercise

November 9, 2021

Binary Classification using Logistic Regression - Excercise

We will predict whether an employee will retain in the company or not.

[50]:
```
# Import necessary package
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

0.0.1 Step 1: Load the dataset

[51]:
```
# Load the dataset into pandas dataframe
df = pd.read_csv("E:\\MY LECTURES\\8.2021-09-03 DATA SCIENCE (KNU)\\3.
↪Programs\\dataset\\HR_comma_sep.csv")
# Change this location based on the location of dataset in your machine
```

[52]:
```
df.head()
```

[52]:
```
   satisfaction_level  last_evaluation  number_project  average_montly_hours  \
0                0.38             0.53               2                   157
1                0.80             0.86               5                   262
2                0.11             0.88               7                   272
3                0.72             0.87               5                   223
4                0.37             0.52               2                   159

   time_spend_company  Work_accident  left  promotion_last_5years Department  \
0                   3              0     1                      0      sales
1                   6              0     1                      0      sales
2                   4              0     1                      0      sales
3                   5              0     1                      0      sales
4                   3              0     1                      0      sales

   salary
0     low
1  medium
2  medium
```

```
3      low
4      low
```

[53]:
```
df.shape
```

[53]: (14999, 10)

0.0.2 Step 2: Apply EDA

How many did leave the company?

[54]:
```
left = df[df.left==1]
left.shape
```

[54]: (3571, 10)

How many are working in the company?

[55]:
```
retained = df[df.left==0]
retained.shape
```

[55]: (11428, 10)

Average numbers for all columns based on insurance buy status

[56]:
```
df.groupby('left').mean()
```

[56]:
```
      satisfaction_level  last_evaluation  number_project  \
left
0               0.666810         0.715473        3.786664
1               0.440098         0.718113        3.855503

      average_montly_hours  time_spend_company  Work_accident  \
left
0               199.060203            3.380032       0.175009
1               207.419210            3.876505       0.047326

      promotion_last_5years
left
0                  0.026251
1                  0.005321
```

From above table we can draw following conclusions,

Satisfaction Level: Satisfaction level seems to be relatively low (0.44) in employees leaving the firm vs the retained ones (0.66)

Average Monthly Hours: Average monthly hours are higher in employees leaving the firm (199 vs 207)

Promotion Last 5 Years: Employees who are given promotion are likely to be retained at firm

Impact of salary on employee retention

[57]:
```
pd.crosstab(df.salary,df.left).plot(kind='bar')
```

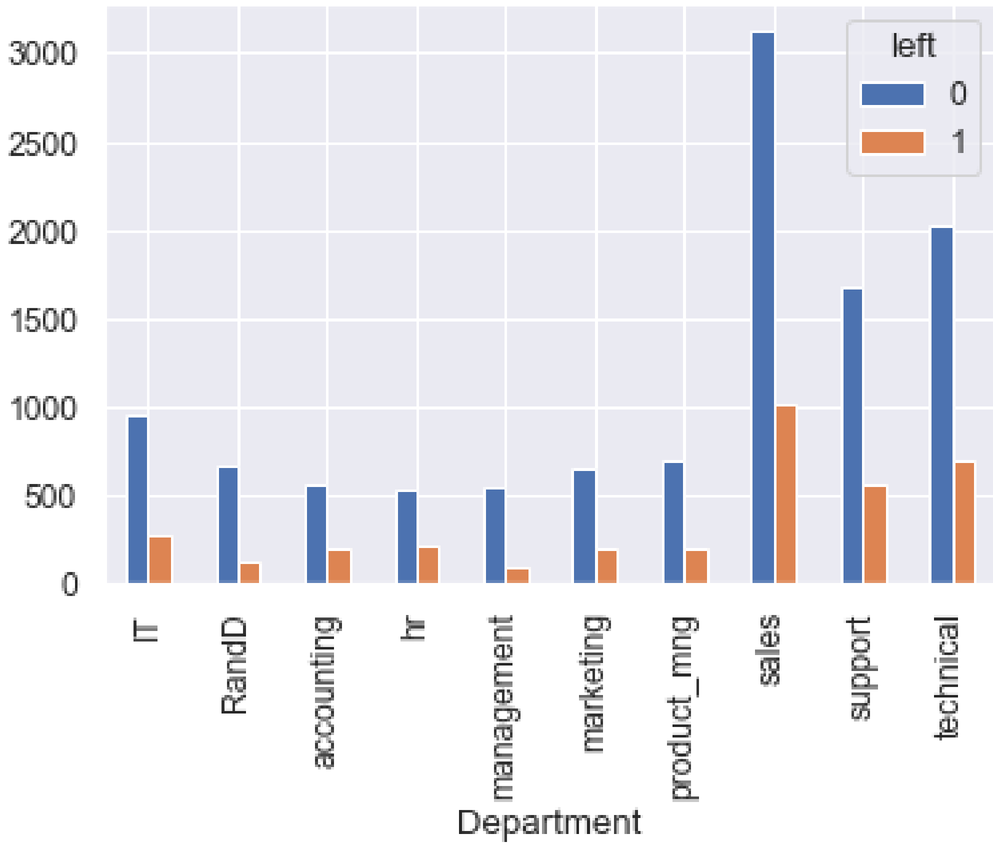
[57]:
```
<AxesSubplot:xlabel='salary'>
```

Above bar chart shows employees with high salaries are likely to not leave the company

Department wise employee retention rate

[58]:
```
pd.crosstab(df.Department,df.left).plot(kind='bar')
```

[58]:
```
<AxesSubplot:xlabel='Department'>
```



From above chart there seem to be some impact of department on employee retention but it is not major hence we will ignore department in our analysis

From the data analysis so far we can conclude that we will use following variables as independant variables in our model.

Satisfaction Level

Average Monthly Hours

Promotion Last 5 Years

Salary

[59]:
```
subdf =␣
↪df[['satisfaction_level','average_montly_hours','promotion_last_5years','salary']]
subdf.head()
```

[59]:

	satisfaction_level	average_montly_hours	promotion_last_5years	salary
0	0.38	157	0	low
1	0.80	262	0	medium
2	0.11	272	0	medium

```
3                 0.72                   223                          0      low
4                 0.37                   159                          0      low
```

0.0.3 Step 3. Pre-process and extract the features

Salary feature has text data. So, introduce dummy variables.

[60]:
```
salary_dummies = pd.get_dummies(subdf.salary, prefix="salary")
df_with_dummies = pd.concat([subdf,salary_dummies],axis='columns')
df_with_dummies.head()
```

[60]:
```
   satisfaction_level  average_montly_hours  promotion_last_5years  salary  \
0                0.38                   157                      0     low
1                0.80                   262                      0  medium
2                0.11                   272                      0  medium
3                0.72                   223                      0     low
4                0.37                   159                      0     low

   salary_high  salary_low  salary_medium
0            0           1              0
1            0           0              1
2            0           0              1
3            0           1              0
4            0           1              0
```

Now we need to remove salary column which is text data as it is already replaced by dummy variables so we can safely remove it

[61]:
```
df_with_dummies.drop('salary',axis='columns',inplace=True)
df_with_dummies.head()
```

[61]:
```
   satisfaction_level  average_montly_hours  promotion_last_5years  \
0                0.38                   157                      0
1                0.80                   262                      0
2                0.11                   272                      0
3                0.72                   223                      0
4                0.37                   159                      0

   salary_high  salary_low  salary_medium
0            0           1              0
1            0           0              1
2            0           0              1
3            0           1              0
4            0           1              0
```

[62]:
```
X = df_with_dummies
X.head()
```

```
[62]:    satisfaction_level  average_montly_hours  promotion_last_5years  \
      0                0.38                   157                      0
      1                0.80                   262                      0
      2                0.11                   272                      0
      3                0.72                   223                      0
      4                0.37                   159                      0

         salary_high  salary_low  salary_medium
      0            0           1              0
      1            0           0              1
      2            0           0              1
      3            0           1              0
      4            0           1              0
```

```
[63]: Y = df.left
```

0.0.4 Step 4. Split the data for training and testing

```
[64]: # Splitting dataset into training and testing 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 = 0)
      #x_train, x_test, y_train, y_test = train_test_split(df[["age"]],df.
       ↪bought_insurance, test_size = 0.2, random_state = 0)
```

0.0.5 Step 5. Training the model

Fitting the model

```
[65]: from sklearn.linear_model import LogisticRegression
      logistic_model = LogisticRegression()
      logistic_model.fit(x_train, y_train)
```

```
[65]: LogisticRegression()
```

```
[66]: logistic_model.coef_     # slope for each feature in log(odds graph)
```

```
[66]: array([[-3.75511715e+00,  2.56224368e-03, -1.17584357e+00,
              -1.00460062e+00,  7.46689080e-01,  2.65460078e-01]])
```

```
[67]: y_train_pred = logistic_model.predict(x_train)
      y_train_pred
```

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

Logistic regression results either 0 or 1 but what could be the calculated value before rounding?

[68]:
```
train_predicted_prob = logistic_model.predict_proba(x_train)
train_predicted_prob
```

[68]:
```
array([[0.87817064, 0.12182936],
       [0.46180007, 0.53819993],
       [0.76783801, 0.23216199],
       …,
       [0.84129841, 0.15870159],
       [0.965606  , 0.034394  ],
       [0.69888883, 0.30111117]])
```

First column is 0 (will not leave), second column is 1 (will will leave). Look at the next cell for the input of following output

Performance score for logistic regression

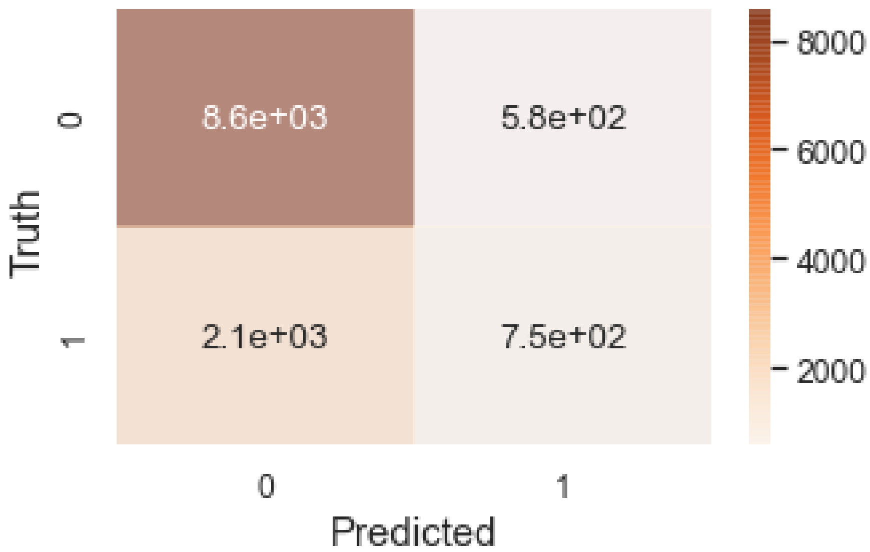
[69]:
```
out = logistic_model.score(x_train,y_train)
Logistic_Train_RS = np.round(out,2)*100
print("Performance score for training set :",Logistic_Train_RS,"%")
```

```
Performance score for training set : 78.0 %
```

Confusion matrix R2 score says the performance of logistic regression over simple probability that does not feature Age. We are interested to know how many has been correctly and wrongly classified.

[70]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_train,y_train_pred)

plt.figure(figsize = (5,3))
sns.set(font_scale=1.1)

axes = plt.gca()
axes.xaxis.label.set_size(15)
axes.yaxis.label.set_size(15)

sns.heatmap(cm, annot=True,cmap=plt.cm.Oranges, alpha=0.5)

plt.xlabel('Predicted')
plt.ylabel('Truth')
```

[70]:
```
Text(19.5, 0.5, 'Truth')
```



Precison, Recall, F1, Accuracy

[71]:
```
# Total report
from sklearn import metrics
print(metrics.classification_report(y_train,y_train_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      0.94      0.86      9129
           1       0.57      0.26      0.36      2870

    accuracy                           0.78     11999
   macro avg       0.68      0.60      0.61     11999
weighted avg       0.74      0.78      0.74     11999
```

[72]:
```
# Accuracy score
temp = metrics.accuracy_score(y_train,y_train_pred)
Logistic_Train_Accuracy = np.round(temp,2)*100
print("Accuracy score : ",Logistic_Train_Accuracy,"%")
```

```
Accuracy score :  78.0 %
```

[73]:
```
# Precision score
temp = metrics.precision_score(y_train,y_train_pred)
Logistic_Train_Precision = np.round(temp,2)*100
print("Precision score : ",Logistic_Train_Precision,"%")
```

```
Precision score :  56.99999999999999 %
```

[74]:
```
# Recall score
temp = metrics.recall_score(y_train,y_train_pred)
Logistic_Train_Recall = np.round(temp,2)*100
print("Recall score : ",Logistic_Train_Recall,"%")
```

```
Recall score :  26.0 %
```

[75]:
```
# F1 score
temp = metrics.f1_score(y_train,y_train_pred)
Logistic_Train_F1 = np.round(temp,2)*100
print("F1 score : ",Logistic_Train_F1,"%")
```

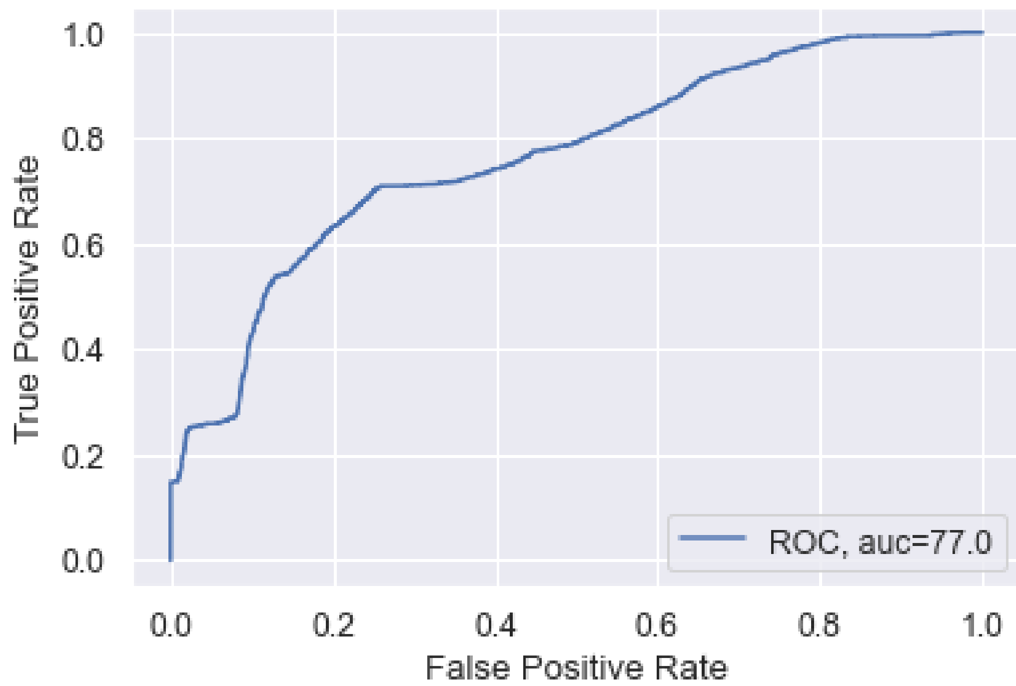
```
F1 score :  36.0 %
```

[76]:
```
# Cohen Kappa score
temp = metrics.cohen_kappa_score(y_train,y_train_pred)
Logistic_Train_CK = np.round(temp,2)*100
print("Cohen Kappa score : ",Logistic_Train_CK,"%")
```

```
Cohen Kappa score :  24.0 %
```

ROC and AUC

[77]:
```
prob = train_predicted_prob[::,1]
fpr, tpr, _ = metrics.roc_curve(y_train, prob)
Logistic_Train_AUC = np.round(metrics.roc_auc_score(y_train, prob),2)*100
plt.plot(fpr,tpr,label="ROC, auc="+str(Logistic_Train_AUC))
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc=4)
plt.show()
```



0.0.6 Step 6. Testing the model

[78]:
```
# Predicting values for test input set
y_test_pred = logistic_model.predict(x_test)
y_test_pred
```

[78]:
```
array([0, 0, 0, …, 0, 0, 1], dtype=int64)
```

[79]:
```
test_predicted_prob = logistic_model.predict_proba(x_test)
test_predicted_prob
# First column is 0 (will not buy) second column is 1 (will buy)
```

[79]:
```
array([[0.73720393, 0.26279607],
       [0.78730394, 0.21269606],
       [0.8705831 , 0.1294169 ],
       …,
       [0.6810017 , 0.3189983 ],
       [0.68875328, 0.31124672],
       [0.43330018, 0.56669982]])
```

Performance score for logistic regression

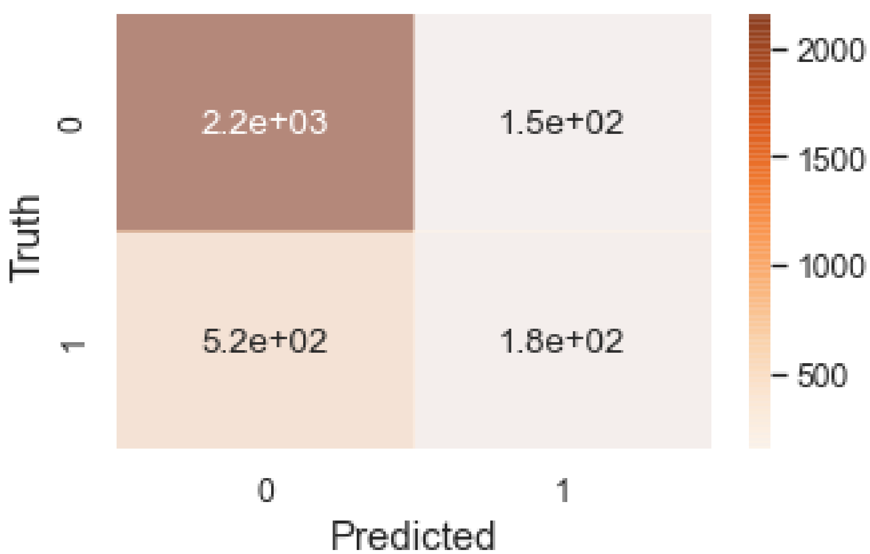
[80]:
```
out = logistic_model.score(x_test,y_test)
Logistic_Test_RS = np.round(out,2)*100
print("Performance score for training set :",Logistic_Test_RS,"%")
```

```
Performance score for training set : 78.0 %
```

Confusion matrix R2 score says the performance of logistic regression over simple probability that does not feature Age. We are interested to know how many has been correctly and wrongly classified.

[81]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,y_test_pred)

plt.figure(figsize = (5,3))
sns.set(font_scale=1.1)

axes = plt.gca()
axes.xaxis.label.set_size(15)
axes.yaxis.label.set_size(15)

sns.heatmap(cm, annot=True,cmap=plt.cm.Oranges, alpha=0.5)

plt.xlabel('Predicted')
plt.ylabel('Truth')
```

[81]: Text(19.5, 0.5, 'Truth')



Precison, Recall, F1, Accuracy

[82]:
```
# Total report
from sklearn import metrics
print(metrics.classification_report(y_test,y_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      0.94      0.87      2299
           1       0.55      0.26      0.35       701

    accuracy                           0.78      3000
   macro avg       0.68      0.60      0.61      3000
weighted avg       0.75      0.78      0.74      3000
```

[83]:
```
# Accuracy score
temp = metrics.accuracy_score(y_test,y_test_pred)
Logistic_Test_Accuracy = np.round(temp,2)*100
print("Accuracy score : ",Logistic_Test_Accuracy,"%")
```

```
Accuracy score :  78.0 %
```

[84]:
```
# Precision score
temp = metrics.precision_score(y_test,y_test_pred)
Logistic_Test_Precision = np.round(temp,2)*100
print("Precision score : ",Logistic_Test_Precision,"%")
```

```
Precision score :  55.00000000000001 %
```

[85]:
```
# Recall score
temp = metrics.recall_score(y_test,y_test_pred)
Logistic_Test_Recall = np.round(temp,2)*100
print("Recall score : ",Logistic_Test_Recall,"%")
```

```
Recall score :  26.0 %
```

[86]:
```
# F1 score
temp = metrics.f1_score(y_test,y_test_pred)
Logistic_Test_F1 = np.round(temp,2)*100
print("F1 score : ",Logistic_Test_F1,"%")
```

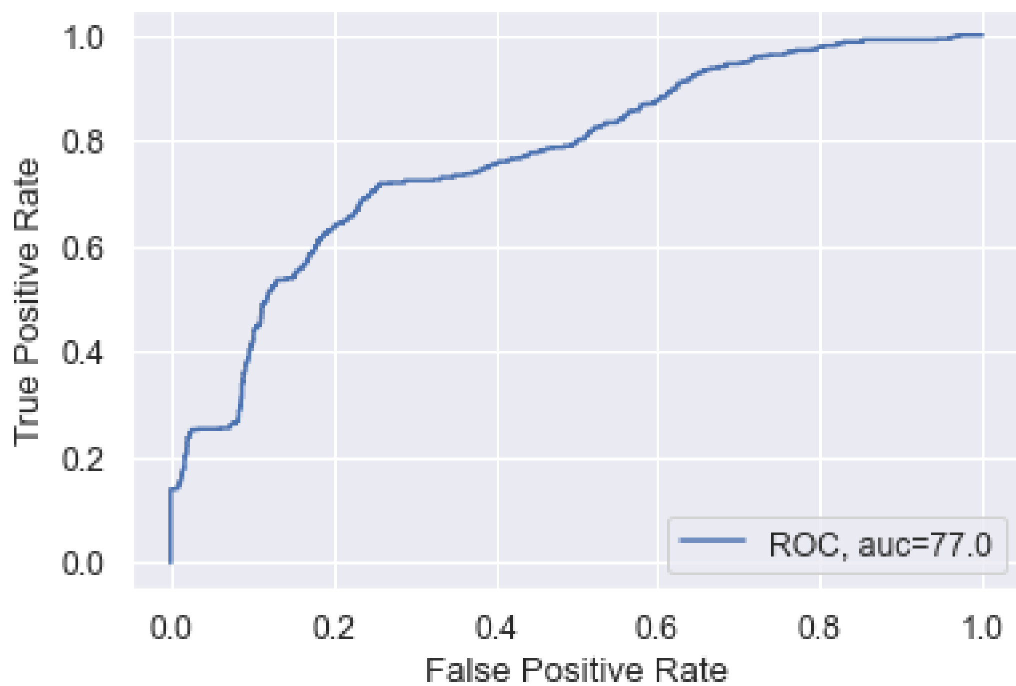
```
F1 score :  35.0 %
```

[87]:
```
# Cohen Kappa score
temp = metrics.cohen_kappa_score(y_test,y_test_pred)
Logistic_Test_CK = np.round(temp,2)*100
print("Cohen Kappa score : ",Logistic_Test_CK,"%")
```

```
Cohen Kappa score :  24.0 %
```

ROC and AUC

[88]:
```
prob = test_predicted_prob[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test, prob)
Logistic_Test_AUC = np.round(metrics.roc_auc_score(y_test, prob),2)*100
plt.plot(fpr,tpr,label="ROC, auc="+str(Logistic_Test_AUC))
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc=4)
plt.show()
```



0.0.7 Step 7. Prediction using the model

Given satisfaction_level, average_montly_hours, promotion_last_5years, salary_high, salary_low, salary_medium as => 0, 0.38, 157, 0, 0, 1, predict an employee will continue job in the company.

[89]:
```
logistic_model.predict([[0,0.38,157,0,0,1]])
```

[89]:
```
array([0], dtype=int64)
```

0.0.8 Step 8. Summary

[90]:
```
print("             Logistic Regression      ")
print("====================================================")
print("\t\tTraining phase       Testing phase ")
print("====================================================")
print("RS\t\t   ",Logistic_Train_RS,"%\t\t", Logistic_Test_RS,"%")
print("Accuracy\t   ",Logistic_Train_Accuracy,"%\t\t",␣
↪Logistic_Test_Accuracy,"%")
print("Precision\t   ",Logistic_Train_Precision,"%\t\t",␣
↪Logistic_Test_Precision,"%")
print("Recall\t\t   ",Logistic_Train_Recall,"%\t\t", Logistic_Test_Recall,"%")
print("F1\t\t   ",Logistic_Train_F1,"%\t\t", Logistic_Test_F1,"%")
print("CK\t\t   ",Logistic_Train_CK,"%\t\t", Logistic_Test_CK,"%")
print("AUC\t\t   ",Logistic_Train_AUC,"%\t\t", Logistic_Test_AUC,"%")
print("====================================================")
```

```
             Logistic Regression
====================================================
                Training phase       Testing phase
====================================================
RS                  78.0 %              78.0 %
Accuracy            78.0 %              78.0 %
Precision           56.99999999999999 %         55.00000000000001 %
Recall              26.0 %              26.0 %
F1                  36.0 %              35.0 %
CK                  24.0 %              24.0 %
AUC                 77.0 %              77.0 %
====================================================
```