PML_Lab-5_205229118_Mahalakshmi.S

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0.0.1 Lab5. Diabetes Classification using Logistic Regression

0.0.2 Step1. [Understand Data]. Using Pandas, import "diabetes.csv" file and print properties such as head, shape, columns, dtype, info and value_counts.

[2]:
```
import pandas as pd
import csv
```

[3]:
```
diab=pd.read_csv("diabetes.csv")
diab
```

[3]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0              6      148             72             35        0  33.6
1              1       85             66             29        0  26.6
2              8      183             64              0        0  23.3
3              1       89             66             23       94  28.1
4              0      137             40             35      168  43.1
..           …        …              …              …        …     …
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4

     DiabetesPedigreeFunction  Age  Outcome
0                       0.627   50        1
1                       0.351   31        0
2                       0.672   32        1
3                       0.167   21        0
4                       2.288   33        1
..                        …    …      …
763                     0.171   63        0
764                     0.340   27        0
765                     0.245   30        0
766                     0.349   47        1
767                     0.315   23        0

[768 rows x 9 columns]
```

[4]:
```
diab.head()
```

[4]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
```

[5]:
```
diab.shape
```

[5]:
```
(768, 9)
```

[6]:
```
df = pd.read_csv("diabetes.csv")
```

[7]:
```
df
```

[7]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0              6      148             72             35        0  33.6
1              1       85             66             29        0  26.6
2              8      183             64              0        0  23.3
3              1       89             66             23       94  28.1
4              0      137             40             35      168  43.1
..           …        …            …            …      …   …
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4

     DiabetesPedigreeFunction  Age  Outcome
0                       0.627   50        1
1                       0.351   31        0
2                       0.672   32        1
3                       0.167   21        0
4                       2.288   33        1
..                        …  …      …
763                     0.171   63        0
764                     0.340   27        0
765                     0.245   30        0
```

```
766                        0.349   47          1
767                        0.315   23          0

[768 rows x 9 columns]
```

[8]:
```
f = df.columns
f
```

[8]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

[9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

[10]:
```
df.dtypes
```

[10]:
```
Pregnancies                   int64
Glucose                       int64
BloodPressure                 int64
SkinThickness                 int64
Insulin                       int64
BMI                         float64
DiabetesPedigreeFunction    float64
Age                           int64
Outcome                       int64
dtype: object
```

[11]:
```
df.dtypes.value_counts()
```

[11]:
```
int64      7
float64    2
```

```
dtype: int64
```

0.0.3 Step2. [Build Logistic Regression Model]

Prepare X matrix (8 feature columns) and y vector (ie., Outcome column)

[12]:
```
X=df.drop("Outcome", axis=1)
y=df[["Outcome"]]
```

[13]:
```
X
```

[13]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0              6      148             72             35        0  33.6
1              1       85             66             29        0  26.6
2              8      183             64              0        0  23.3
3              1       89             66             23       94  28.1
4              0      137             40             35      168  43.1
..           …        …            …            …      …    …
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4

     DiabetesPedigreeFunction  Age
0                       0.627   50
1                       0.351   31
2                       0.672   32
3                       0.167   21
4                       2.288   33
..                        …  …
763                     0.171   63
764                     0.340   27
765                     0.245   30
766                     0.349   47
767                     0.315   23

[768 rows x 8 columns]
```

[14]:
```
y
```

[14]:
```
     Outcome
0          1
1          0
2          1
3          0
4          1
..       …
```

```
763        0
764        0
765        0
766        1
767        0

[768 rows x 1 columns]
```

Split dataset with stratified shuffle split for training and testing as X_train, X_test, y_train, y_test (use 25% test size).

[15]:
```
from sklearn.model_selection import StratifiedShuffleSplit
```

[16]:
```
StratifiedShuffleSplit()
shuf = StratifiedShuffleSplit(n_splits=4, test_size=0.25,random_state=0)
```

[17]:
```
shuf.get_n_splits(X,y)
```

[17]: 4

Create LogisticRegression model, fit on training set and predict on test set

[18]:
```
import warnings
warnings.filterwarnings('ignore')
```

[19]:
```
for train, test in shuf.split(X, y):
    X_train, X_test = X.iloc[train], X.iloc[test]
    y_train, y_test = y.iloc[train], y.iloc[test]
```

[20]:
```
from sklearn.linear_model import LogisticRegression
```

[21]:
```
logmodel = LogisticRegression()
```

[22]:
```
logmodel.fit(X_train,y_train)
```

[22]: LogisticRegression()

[23]:
```
y_predic = logmodel.predict(X_test)
y_predic
```

[23]:
```
array([0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
       1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1,
       0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0], dtype=int64)
```

[24]:
```
logmodel.score(X_train,y_train)
```

[24]: 0.7899305555555556

0.0.4 Step3. [Predict on a new sample]

Will this person become diabetic?. His details are given below.

new_person = [[6, 200, 90, 10, 25, 23.3, 0.672, 42]]

[25]:
```
new_person = [[6, 200, 90, 10, 25, 23.3, 0.672, 42]]
```

[26]:
```
print(logmodel.predict(new_person))
```

```
[1]
```

0.0.5 Step3. [Compute Classification Metrics]

Compute and print Accuracy, Precision, Recall and AUC scores

0.0.6 Precision

[27]:
```
from sklearn.metrics import precision_score
print(precision_score(y_test, y_predic))
```

```
0.6727272727272727
```

0.0.7 Recall

[28]:
```
from sklearn.metrics import recall_score
print(recall_score(y_test, y_predic))
```

```
0.5522388059701493
```

0.0.8 Accuracy

[29]:
```
from sklearn.metrics import accuracy_score
log_acscore=accuracy_score(y_test, y_predic)
```

[30]:
```
log_acscore
```

[30]: 0.75

0.0.9 AUC scores

[31]:
```
from sklearn.metrics import roc_auc_score
```

[33]:
```
print(roc_auc_score(y_test, y_predic))
```

```
0.7041194029850747
```

0.0.10 Step4. [Understand Correlation]

Create confusion matrix between y__test and y__pred and plot confusion matrix values in a Heatmap. Explain the meaning of the 4 numbers you get.

[35]:
```python
from sklearn.metrics import confusion_matrix
confu_matrix=confusion_matrix(y_test, y_predic)
confu_matrix
```

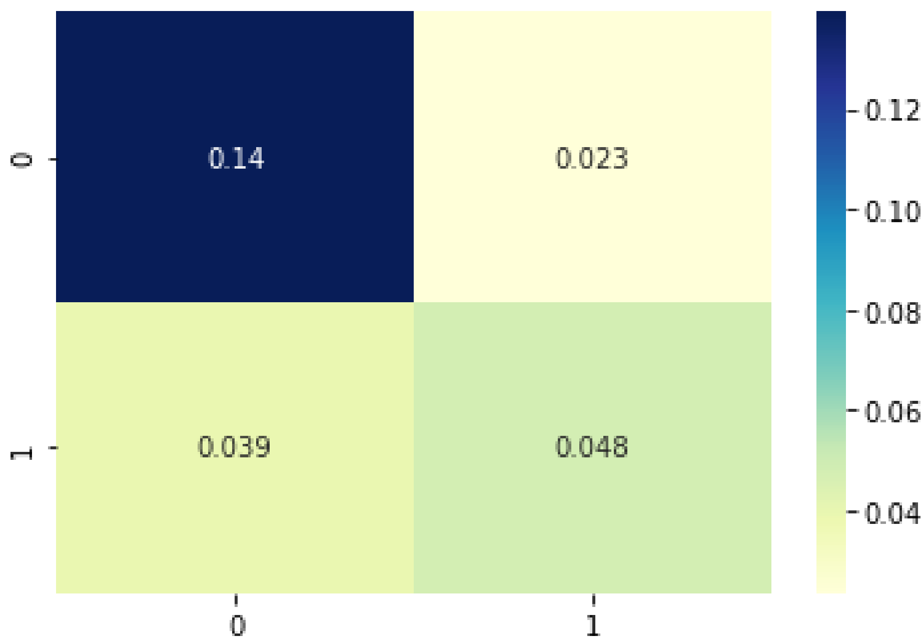
[35]:
```
array([[107,  18],
       [ 30,  37]], dtype=int64)
```

[37]:
```python
confu_accu_score = accuracy_score(y_test, y_predic)
confu_accu_score
```

[37]:
```
0.75
```

[38]:
```python
import seaborn as sns
sns.heatmap(confusion_matrix(y_test,y_predic) / len(y), cmap='YlGnBu',␣
 ↪annot=True)
```

[38]:
```
<AxesSubplot:>
```



0.0.11 Step5. [Normalization using MinmaxScaler and rebuild LoR]

Now, normalize your X__train and X__test values using MinmaxScaler

[39]:
```python
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
```

```
X_trained_min = scaler.fit_transform(X_train)
X_tested_min = scaler.transform(X_test)
```

[40]:
```
X_trained_min.shape
```

[40]: (576, 8)

[41]:
```
X_tested_min.shape
```

[41]: (192, 8)

Create a new LogisticRegression model, fit on normalized training set and predict on the normalized test set

[42]:
```
from sklearn.linear_model import LogisticRegression
logmodel1 = LogisticRegression()
```

[44]:
```
logmodel1.fit(X_trained_min, y_train)
```

[44]: LogisticRegression()

[45]:
```
y_predict = logmodel1.predict(X_tested_min)
y_predict
```

[45]:
```
array([0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
       1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1,
       0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0], dtype=int64)
```

[46]:
```
logmodel1.score(X_trained_min, y_train)
```

[46]: 0.7899305555555556

0.0.12 Compute and print Accuracy, Precision, Recall and AUC scores

0.0.13 Precision

[47]:
```
from sklearn.metrics import precision_score
print(precision_score(y_test, y_predict))
```

0.673469387755102

0.0.14 Recall

[49]:
```
from sklearn.metrics import recall_score
print(recall_score(y_test, y_predict))
```

```
0.4925373134328358
```

0.0.15 Accuracy

[50]:
```
from sklearn.metrics import accuracy_score
min_accscore=accuracy_score(y_test, y_predict)
```

[51]:
```
min_accscore
```

[51]:
```
0.7395833333333334
```

0.0.16 AUC scores

[52]:
```
from sklearn.metrics import roc_auc_score
```

[56]:
```
log_auc_sc=roc_auc_score(y_test, y_predict)
log_auc1=('LoR minmax, AUC=',log_acscore)
log_auc1
```

[56]:
```
('LoR minmax, AUC=', 0.75)
```

0.0.17 Step6. [Normalization using StandardScaler and rebuild LoR]

Repeat Step5 with StandardScaler

[57]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_trained_stand = scaler.fit_transform(X_train)
X_tested_stand = scaler.transform(X_test)
```

[59]:
```
X_trained_stand.shape
```

[59]:
```
(576, 8)
```

[60]:
```
X_tested_stand.shape
```

[60]:
```
(192, 8)
```

[61]:
```
from sklearn.linear_model import LogisticRegression
logmodel2 = LogisticRegression()
```

[63]:
```
logmodel2.fit(X_trained_stand, y_train)
```

[63]:
```
LogisticRegression()
```

[66]:
```
y_predict_stand = logmodel2.predict(X_tested_stand)
y_predict_stand
```

[66]:
```
array([0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
       1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1,
       0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0], dtype=int64)
```

[67]:
```
logmodel2.score(X_trained_stand, y_train)
```

[67]:
```
0.7795138888888888
```

0.0.18 Precision score

[68]:
```
from sklearn.metrics import precision_score
print(precision_score(y_test, y_predict_stand))
```

```
0.6851851851851852
```

0.0.19 Recall score

[69]:
```
from sklearn.metrics import recall_score
print(recall_score(y_test, y_predict_stand))
```

```
0.5522388059701493
```

0.0.20 Accuracy

[70]:
```
from sklearn.metrics import accuracy_score
stand_accscore=accuracy_score(y_test, y_predict_stand)
```

[71]:
```
stand_accscore
```

[71]:
```
0.7552083333333334
```

0.0.21 AUC score

[72]:
```
from sklearn.metrics import roc_auc_score
```

[73]:
```
stand_aucscore=roc_auc_score(y_test, y_predict_stand)
stand_auc3=('AUC=',stand_aucscore)
stand_auc3
```

[73]:
```
('AUC=', 0.7081194029850746)
```

0.0.22 Among the 3 models, which model gives better classification scores?

[74]:
```
print('Logistic Regression Model:',log_acscore)
print('MinmaxScaler:',min_accscore)
print('StandardScaler:',stand_accscore)
```

```
Logistic Regression Model: 0.75
MinmaxScaler: 0.7395833333333334
StandardScaler: 0.7552083333333334
```

0.0.23 Step7. [Plot ROC curve]

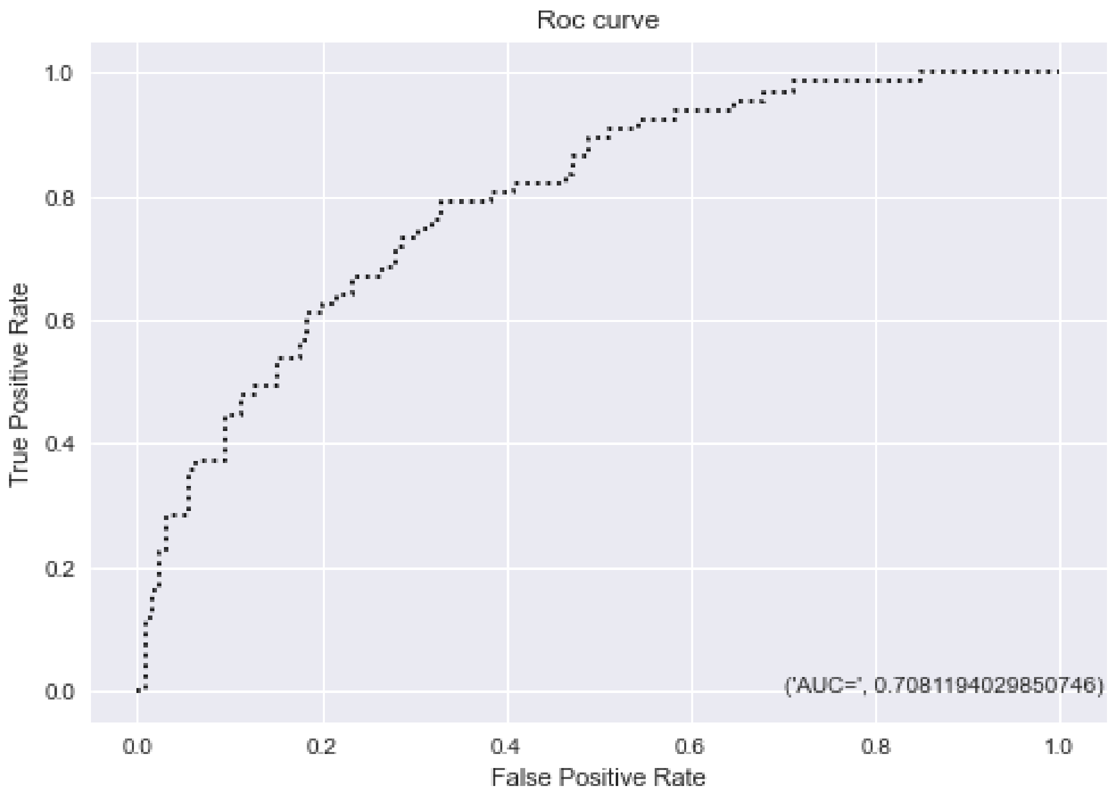
Plot ROC curve as shown below. You can use the MinmaxScaler scaled values of X_test for computing predict_proba() score.¶

[75]:
```
from sklearn.metrics import roc_curve
```

[77]:
```
pred_prb3 = logmodel1.predict_proba(X_tested_min)
fprb3, tprb3, threshold3 = roc_curve(y_test,pred_prb3[:,1], pos_label=1)
```

[78]:
```
import matplotlib.pyplot as plt
plt.style.use('seaborn')
plt.annotate(xy=[0.7,0], s=stand_auc3)
plt.plot(fpr1, tpr1, linestyle=':', color='black',label='Logistic Regression')
plt.title('Roc curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
```

[78]:
```
Text(0, 0.5, 'True Positive Rate')
```



0.0.24 Step8. [Comparison with KNN classifier].

Create a KNN classifier with default values, fit on the scaled X using MinmaxScaler, predict and print classification metric scores.

[79]:
```
from sklearn.neighbors import KNeighborsClassifier
```

[80]:
```
logmodel3 = KNeighborsClassifier(n_neighbors=3)
```

[81]:
```
logmodel3.fit(X_trained_min,y_train)
```

[81]:
```
KNeighborsClassifier(n_neighbors=3)
```

[82]:
```
knn_y_pred = logmodel3.predict(X_tested_min)
knn_y_pred
```

[82]:
```
array([1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
       1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0,
       1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0,
```

```
0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0,
0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1], dtype=int64)
```

0.0.25 Precision score

[83]:
```
from sklearn.metrics import precision_score
print(precision_score(y_test, knn_y_pred))
```

```
0.6271186440677966
```

0.0.26 Recall score

[84]:
```
from sklearn.metrics import recall_score
print(recall_score(y_test, knn_y_pred))
```

```
0.5522388059701493
```

0.0.27 Accuracy

[85]:
```
from sklearn.metrics import accuracy_score
knn_accscore=accuracy_score(y_test, knn_y_pred)
knn_accscore
```

[85]:
```
0.7291666666666666
```

0.0.28 AUC score

[87]:
```
from sklearn.metrics import roc_auc_score
knn_aucscore=roc_auc_score(y_test, knn_y_pred)
knn_auc2=('KNN minmax, AUC=',knn_aucscore)
knn_auc2
```

[87]:
```
('KNN minmax, AUC=', 0.6881194029850747)
```

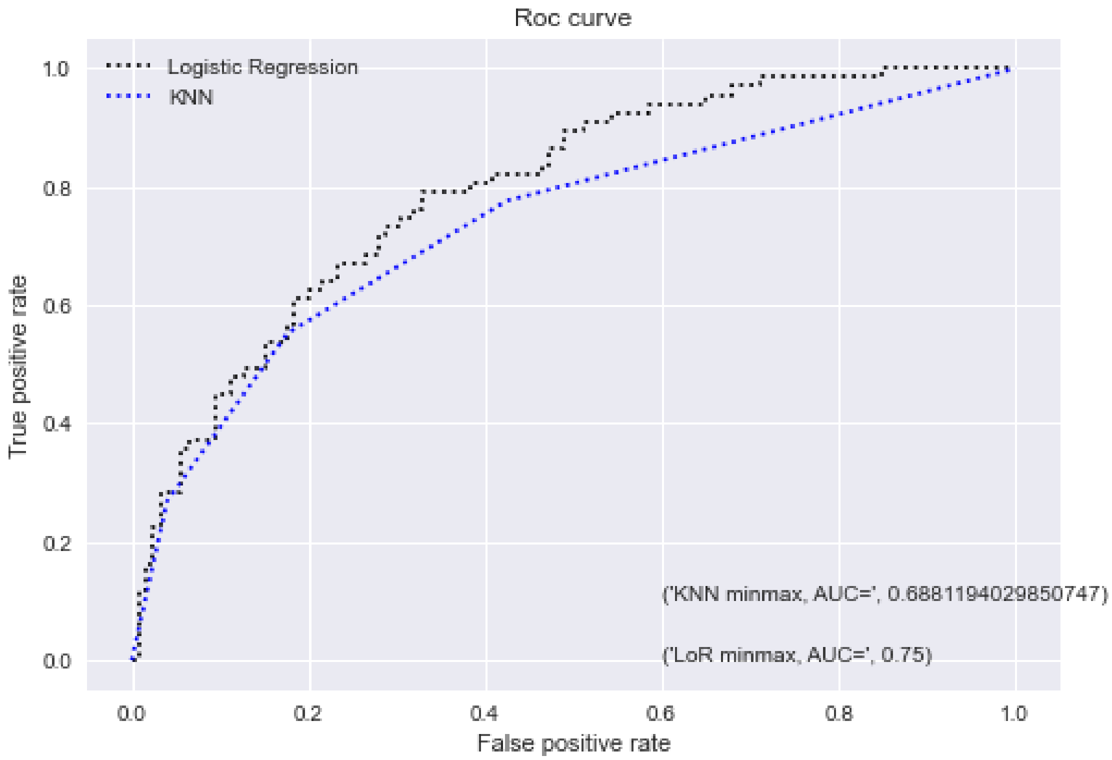
0.0.29 Step9. [Update ROC curve]

Update your ROC curve, this time, with one more curve of KNN classifier

[89]:
```
pred_prb2 = logmodel3.predict_proba(X_tested_min)
fprb3,tprb3,threshold1 = roc_curve(y_test, pred_prb3[:,1],pos_label=1)
fprb2,tprb2,threshold2 = roc_curve(y_test, pred_prb2[:,1],pos_label=1)
```

[91]:
```
plt.plot(fprb3,tprb3,linestyle=':',color='black',label='Logistic Regression')
plt.plot(fprb2,tprb2,linestyle=':',color ='blue',label='KNN')
plt.annotate(xy=[0.6,0.1], s=knn_auc2)
plt.annotate(xy=[0.6,0], s=log_auc1)
plt.legend(loc='best')
plt.title('Roc curve')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
```

[91]: Text(0, 0.5, 'True positive rate')



0.0.30 Step10. [Regularization]

In order to reduce overfitting of your data, you will use LogisticRegressionCV model with L1 and L2 regularization parameters. Create both models using the following statements

[92]:
```
from sklearn.linear_model import LogisticRegressionCV
```

[93]:
```
logmodel4 = LogisticRegressionCV(Cs=10, cv=4, penalty='l1', solver='liblinear')
logmodel5 = LogisticRegressionCV(Cs=10, cv=4, penalty='l2')
```

Perform fit using MinmaxScaler scaled values and predict¶

[94]:
```
print(logmodel4.fit(X_trained_min,y_train))
print(logmodel5.fit(X_trained_min,y_train))
```

```
LogisticRegressionCV(cv=4, penalty='l1', solver='liblinear')
LogisticRegressionCV(cv=4)
```

[97]:
```
logrg_y_pred5 = logmodel4.predict(X_tested_min)
logrg_y_pred6 = logmodel5.predict(X_tested_min)
print('Logistic RegressionCV L1:\n',logrg_y_pred5)
print('#####################################################################################
```

```
print('Logistic RegressionCV L2:\n',logrg_y_pred6)
```

```
Logistic RegressionCV L1:
 [0 0 1 1 0 1 1 0 0 1 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0
 0 0 0 0 1 0 1 1 0 1 0 1 0 0 0 1 0 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0
 1 0 0 0 0 1 1 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 1 0
 0 0 1 1 0 0 0 0 0 1 0 0 1 1 0 0 0 0 0 0 1 0 1 1 1 1 0 0 0 0 0 0 1 0 0 0
 1 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 1 0 0 1 1 0 0
 0 0 0 1 0 0 0]
################################################################################
##############
Logistic RegressionCV L2:
 [0 0 1 1 0 1 1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0
 0 0 0 0 1 0 1 1 0 1 0 1 0 0 0 1 0 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 1
 1 0 0 0 0 1 1 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 1 0
 0 0 1 1 0 0 0 0 0 1 0 0 1 1 0 0 0 0 0 0 1 0 1 1 1 1 0 0 0 1 0 0 1 0 0 0
 1 1 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 1 0 1 0 0 1 0 0 0 0 0 1 0 0 1 1 0 0
 0 0 0 1 0 0 0]
```

[98]:
```
from sklearn.metrics import roc_auc_score
logrgpred_auc=roc_auc_score(y_test,logrg_y_pred5)
logrgpred4_auc=('LoR L1 minmax, AUC=',logrgpred_auc)
logrgpred4_auc
```

[98]:
```
('LoR L1 minmax, AUC=', 0.6748059701492537)
```

[99]:
```
from sklearn.metrics import roc_auc_score
logrgpred_auc1=roc_auc_score(y_test, logrg_y_pred6)
logrgpred5_auc=('LoR L2 minmax, AUC=',logrgpred_auc1)
logrgpred5_auc
```

[99]:
```
('LoR L2 minmax, AUC=', 0.6931940298507463)
```

0.0.31 Step11. [Update ROC curve]

Update your ROC curve, this time, with two more curves

[101]:
```
pred_prb7 = logmodel4.predict_proba(X_tested_min)
pred_prb8 = logmodel5.predict_proba(X_tested_min)
fprb2,tprb2,threshold2 = roc_curve(y_test, pred_prb2[:,1],pos_label=1)
fprb3,tprb3,threshold1 = roc_curve(y_test, pred_prb3[:,1],pos_label=1)
fprb5,tprb5,thresh3 = roc_curve(y_test, pred_prb7[:,1],pos_label=1)
fprb6,tprb6,thresh4 = roc_curve(y_test, pred_prb8[:,1],pos_label=1)
```

[102]:
```
plt.plot(fprb2,tprb2,linestyle='-',color='midnightblue', label='Logistic␣
 ↪Regression')
plt.plot(fprb3,tprb3,linestyle='-',color='black', label='KNN')
plt.plot(fprb5,tprb5,linestyle='-',color='red', label='LoR L1')
plt.plot(fprb6,tprb6,linestyle='-',color='forestgreen', label='LoR L2')
```

```
plt.annotate(xy=[0.49,0.3], s=knn_auc2)
plt.annotate(xy=[0.49,0.2], s=log_auc1)
plt.annotate(xy=[0.49,0.1], s=logrgpred4_auc)
plt.annotate(xy=[0.49,0], s=logrgpred5_auc)
plt.legend(loc='best')
plt.title('ROC curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True  Positive Rate')
```

[102]: Text(0, 0.5, 'True Positive Rate')