Naive Bayes- K-Nearest Neighbors classifier

March 2, 2022

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import sys
import os
import csv
import warnings
warnings.filterwarnings("ignore")

import plotly.offline as py
from plotly.offline import init_notebook_mode, iplot
import plotly.graph_objs as go
from plotly import tools
init_notebook_mode(connected = True)
import plotly.figure_factory as ff
from sklearn.model_selection import train_test_split


import random
import math

from sklearn import datasets
from sklearn import metrics
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
```

[2]:
```
#Read the data
data= pd.read_csv("/Users/aminameghezzi/Downloads/dataset12.csv", sep=',')
data
```

[2]:

	Unnamed: 0	University	Major	Decision	GRE_SCORE	GRE Quant	\
0	2	50	0	1	315.0	158.0	
1	3	50	0	1	301.0	151.0	
2	4	50	0	1	311.0	156.0	
3	5	50	0	1	312.0	156.0	
4	6	50	0	1	307.0	154.0	

```
…          …          …    …       …         …         …
1609         445          293      1         0      284.0      140.0
1610         446          293      1         0      293.0      152.0
1611         447          293      1         0      306.0      157.0
1612         448          293      1         0      296.0      147.0
1613         449          290      1         0      295.0      147.0

      GRE Verbal  work_ex          Name     GPA  Language Proficiency
0          157.0      3.0     bostonner  77.000                   7.5
1          150.0     60.0    KrithikaCT  80.120                   0.0
2          155.0     25.0   Giridhar312  66.954                   7.0
3          156.0     24.0    Shreepriya  73.060                   8.0
4          153.0     34.0       muktika  68.800                   7.5
…          …      …            …     …                      …
1609       144.0      NaN         Aryan  68.000                   6.5
1610       141.0      NaN    Shrinivass  61.700                   6.0
1611       149.0      NaN  Suhaib Siraj  63.170                   7.5
1612       149.0      NaN         Mohan  65.000                   6.5
1613       148.0      6.0         Mohan  64.000                   6.5

[1614 rows x 11 columns]
```

[3]:
```
data.drop(columns=['Unnamed: 0','Name'], inplace=True)
data
```

[3]:
```
      University  Major  Decision  GRE_SCORE  GRE Quant  GRE Verbal  work_ex  \
0             50      0         1      315.0      158.0       157.0      3.0
1             50      0         1      301.0      151.0       150.0     60.0
2             50      0         1      311.0      156.0       155.0     25.0
3             50      0         1      312.0      156.0       156.0     24.0
4             50      0         1      307.0      154.0       153.0     34.0
…          …    …       …         …        …       …
1609         293      1         0      284.0      140.0       144.0      NaN
1610         293      1         0      293.0      152.0       141.0      NaN
1611         293      1         0      306.0      157.0       149.0      NaN
1612         293      1         0      296.0      147.0       149.0      NaN
1613         290      1         0      295.0      147.0       148.0      6.0

         GPA  Language Proficiency
0     77.000                   7.5
1     80.120                   0.0
2     66.954                   7.0
3     73.060                   8.0
4     68.800                   7.5
…      …                      …
1609  68.000                   6.5
1610  61.700                   6.0
```

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1611  63.170                   7.5
1612  65.000                   6.5
1613  64.000                   6.5

[1614 rows x 9 columns]
```

[4]:
```
#drop the nan values
data.dropna(inplace = True)
#check if we have nan values
data.isnull().any().any()
```

[4]:
```
False
```

[5]:
```
data
```

[5]:
```
      University  Major  Decision  GRE_SCORE  GRE Quant  GRE Verbal  work_ex  \
0             50      0         1      315.0      158.0       157.0      3.0
1             50      0         1      301.0      151.0       150.0     60.0
2             50      0         1      311.0      156.0       155.0     25.0
3             50      0         1      312.0      156.0       156.0     24.0
4             50      0         1      307.0      154.0       153.0     34.0
…            …    …       …         …          …          …      …
1598          46      1         0      328.0      165.0       163.0      5.0
1599          46      0         0      309.0      167.0       142.0      0.0
1601         111      1         0      295.0      155.0       140.0      0.0
1608         293      1         0      280.0      150.0       130.0      1.0
1613         290      1         0      295.0      147.0       148.0      6.0

          GPA  Language Proficiency
0     77.000                   7.5
1     80.120                   0.0
2     66.954                   7.0
3     73.060                   8.0
4     68.800                   7.5
…      …                      …
1598  85.000                   8.5
1599  66.173                   6.5
1601  68.000                   6.5
1608  75.000                   5.5
1613  64.000                   6.5

[1448 rows x 9 columns]
```

[6]:
```
#split the dataset into training ans testing sets
def  splitdataset(data):

    targets = data["Decision"].values
```

```
    features= data.drop(["Decision"],axis=1)

    features_train, features_test,target_train, target_test=␣
 ↪train_test_split(features ,targets, test_size = 0.3, random_state = 100)
    return features,targets ,features_train, features_test,target_train,␣
 ↪target_test
```

[7]:
```
#function to tarin the dataset using naive bayse approch
def NBClassifier(features_train,target_train):
    model= GaussianNB()
    model.fit(features_train,target_train)

    return model
```

[8]:
```
#function to make predection
def prediction(X_test, model):


    predicted=model.predict(X_test)
    print("Predicted values:")
    for item in zip(target_test,predicted):
        print('actual was ', item[0], 'predection was',item[1])
    return predicted
```

[9]:
```
#calculating the Presion, Recall and Accuracy

features,targets ,features_train, features_test,target_train, target_test=␣
 ↪splitdataset(data)
model = NBClassifier(features_train,target_train)
predicted=prediction(features_test, model)
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Predicted values:
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[10]:
```
print(metrics.classification_report(target_test, predicted))
print(metrics.confusion_matrix(target_test, predicted))

print ("Accuracy : ", accuracy_score(target_test, predicted)*100)
```

```
              precision    recall  f1-score   support

           0       0.51      0.97      0.67       211
```

```
           1       0.79      0.12      0.20       224

    accuracy                           0.53       435
   macro avg       0.65      0.54      0.43       435
weighted avg       0.65      0.53      0.43       435

[[204   7]
 [198  26]]
Accuracy :  52.87356321839081
```

[46]:
```
#ploting the confusion matrics
conf_matrix= plt.subplot()
labels=[0, 1]
cm = metrics.confusion_matrix(target_test, predicted)
print(predicted)

columns=['Admit', 'Reject']
index=['Admit', 'Reject']
cm_df = pd.DataFrame(cm,columns,index)
sns.heatmap(cm_df, annot=True,ax=conf_matrix, fmt='g', center=True);␣
 ↪#annot=True to annotate cells
conf_matrix.set_xlabel('Predicted labels');conf_matrix.set_ylabel('True␣
 ↪labels');
conf_matrix.set_title('Confusion Matrix');
conf_matrix.xaxis.set_ticklabels(['Admit', 'Reject']); conf_matrix.yaxis.
 ↪set_ticklabels(['Admit', 'Reject']);


#print("Confusion Matrix: \n", confusion_matrix(y_test, y_pred))
print ("Accuracy : ", accuracy_score(target_test, predicted)*100)
```

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Accuracy :  52.87356321839081
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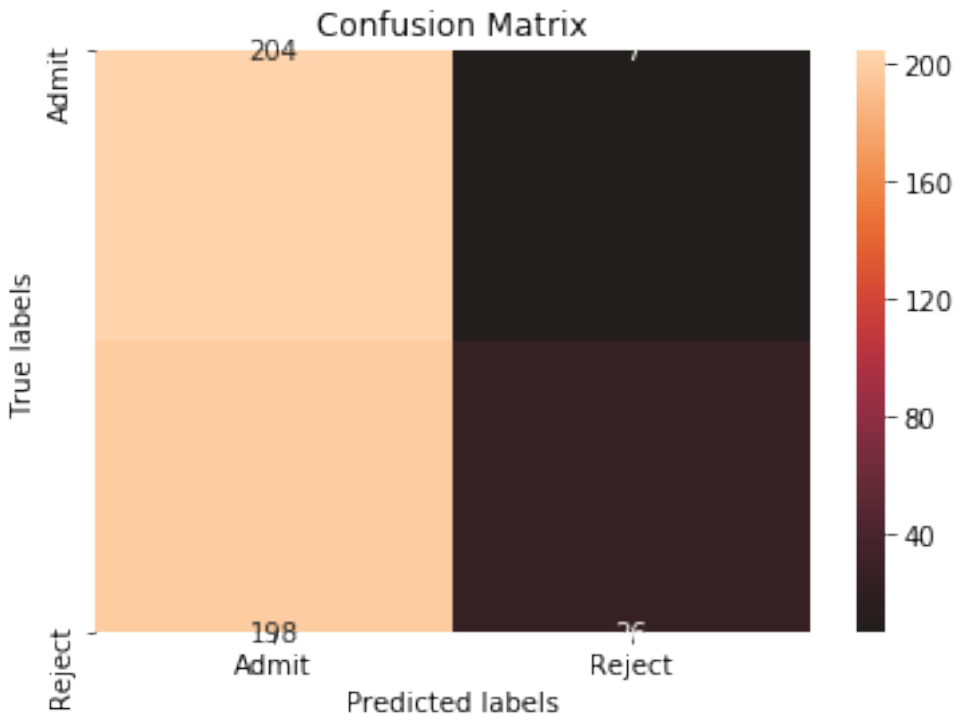
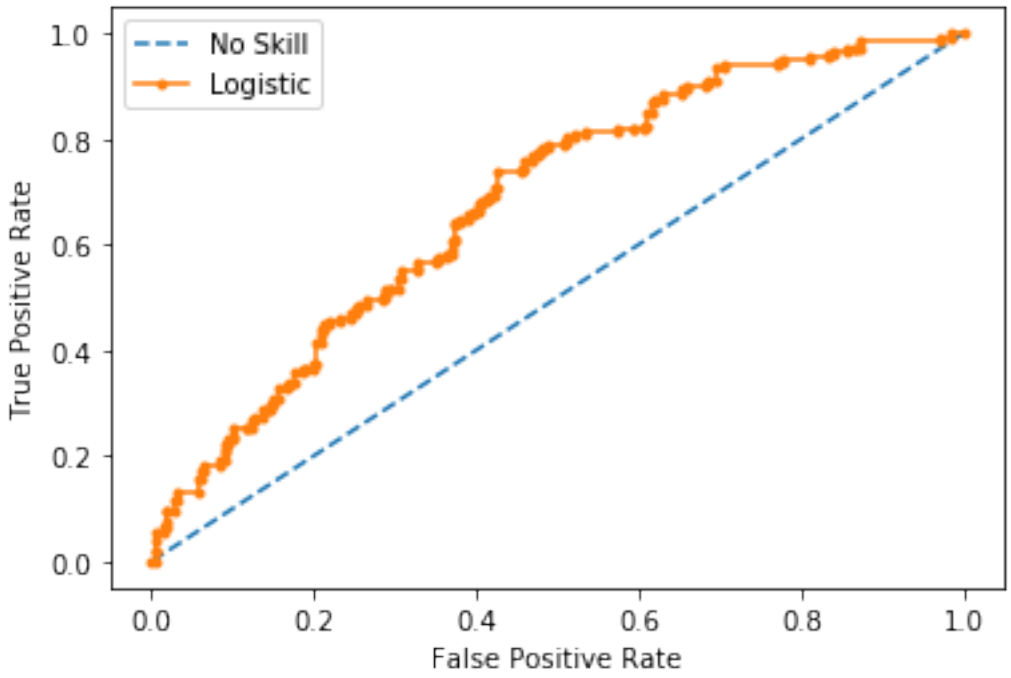


[11]:
```
# roc curve and auc

from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from matplotlib import pyplot

# generate a no skill prediction (majority class)
ns_probs = [0 for _ in range(len(target_test))]
# fit a model
#model = LogisticRegression(solver='lbfgs')
#model.fit(trainX, trainy)
model= NBClassifier(features_train,target_train)

#lr_probs = model.predict_proba(testX)
lr_probs=model.predict_proba(features_test)
# keep probabilities for the positive outcome only
lr_probs = lr_probs[:, 1]
# calculate scores
ns_auc = roc_auc_score(target_test, ns_probs)
lr_auc = roc_auc_score(target_test, lr_probs)
# summarize scores
print('No Skill: ROC AUC=%.3f' % (ns_auc))
print('Logistic: ROC AUC=%.3f' % (lr_auc))
```

```
# calculate roc curves
ns_fpr, ns_tpr, _ = roc_curve(target_test, ns_probs)
lr_fpr, lr_tpr, _ = roc_curve(target_test, lr_probs)
# plot the roc curve for the model
pyplot.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
pyplot.plot(lr_fpr, lr_tpr, marker='.', label='Logistic')
# axis labels
pyplot.xlabel('False Positive Rate')
pyplot.ylabel('True Positive Rate')
# show the legend
pyplot.legend()
# show the plot
pyplot.show()
```

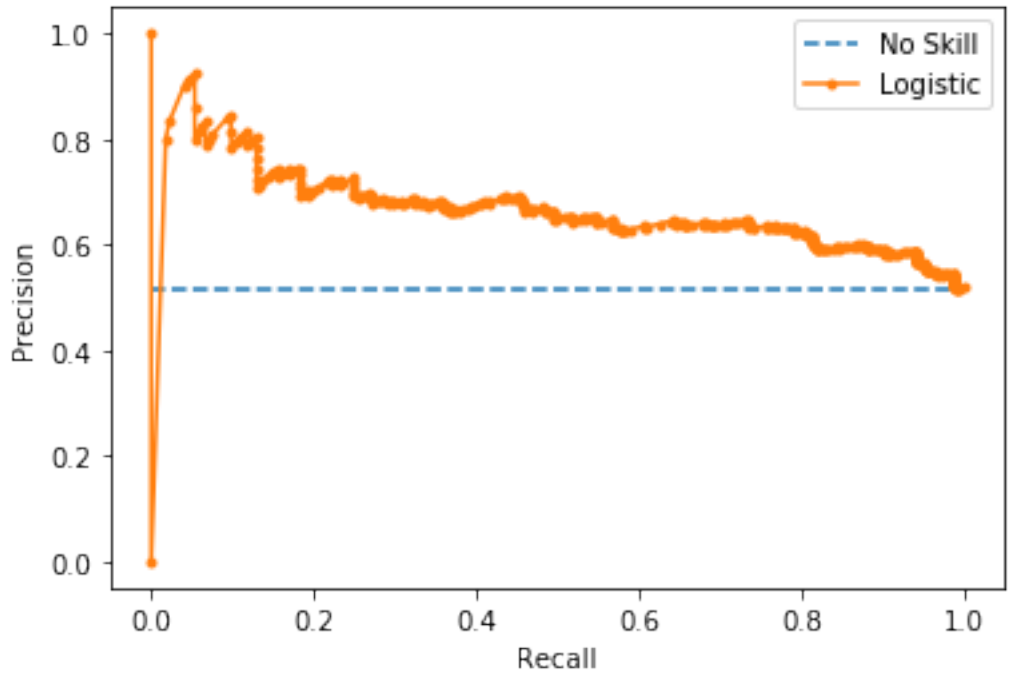
```
No Skill: ROC AUC=0.500
Logistic: ROC AUC=0.683
```



[12]:
```
# precision-recall curve and f1

from sklearn.metrics import precision_recall_curve
from sklearn.metrics import f1_score
from sklearn.metrics import auc
from matplotlib import pyplot

model= NBClassifier(features_train,target_train)
```

```
# predict probabilities
lr_probs = model.predict_proba(features_test)
# keep probabilities for the positive outcome only
lr_probs = lr_probs[:, 1]
# predict class values
yhat = model.predict(features_test)
lr_precision, lr_recall, _ = precision_recall_curve(target_test, lr_probs)
lr_f1, lr_auc = f1_score(target_test, yhat), auc(lr_recall, lr_precision)
# summarize scores
print('Logistic: f1=%.3f auc=%.3f' % (lr_f1, lr_auc))
# plot the precision-recall curves
no_skill = len(target_test[target_test==1]) / len(target_test)
pyplot.plot([0, 1], [no_skill, no_skill], linestyle='--', label='No Skill')
pyplot.plot(lr_recall, lr_precision, marker='.', label='Logistic')
# axis labels
pyplot.xlabel('Recall')
pyplot.ylabel('Precision')
# show the legend
pyplot.legend()
# show the plot
pyplot.show()
```

```
Logistic: f1=0.202 auc=0.664
```



[68]:

[13]:
```
#spliting the dataset to prepare it KNN classifier
x,y,x_train, x_test, y_train, y_test = splitdataset(data)
```

[14]:
```
#scale the features so that all of them can be uniformly evaluated
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(x_train)

X_train = scaler.transform(x_train)
X_test = scaler.transform(x_test)
```

[15]:
```
y_train_label = [1 if each > 0.8 else 0 for each in y_train]
y_test_label  = [1 if each > 0.8 else 0 for each in y_test]
```

[27]:
```
math.sqrt(len(y_test_label))
```

[27]:
```
20.85665361461421
```

[16]:
```
#trainning and predecting using K_Nearest NeighborsClassifier
from sklearn.neighbors import KNeighborsClassifier
knnc = KNeighborsClassifier(n_neighbors = 5, p=2, metric = 'euclidean')
print(knnc.fit(x_train, y_train_label))
y_pred_knn = knnc.predict(x_test)
y_pred_knn
```

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='euclidean',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                     weights='uniform')
```

[16]:
```
array([1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0,
       0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0,
       1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1,
       1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0,
       1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0,
       1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1,
       1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0,
       0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0,
       0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1,
       1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1,
       0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0,
       0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0,
       1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 0,
       0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1,
       0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1,
       0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1,
```

```
       1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0])
```

[47]:
```
print(y_pred_knn)
```

```
[1 0 1 0 0 1 0 1 1 0 0 0 0 1 0 1 1 1 1 1 0 0 0 0 1 0 0 1 0 1 1 0 1 0 0 0 1
 1 0 0 0 0 0 1 1 1 0 1 0 1 0 1 1 0 1 1 1 1 1 0 0 1 1 0 1 1 1 0 1 0 0 1 0 1 1 0
 0 0 0 1 1 1 0 1 1 1 1 1 1 1 0 1 0 1 1 1 0 0 0 0 0 0 1 1 1 0 0 0 1 1 0 1 0 0
 1 1 1 0 1 0 1 0 0 0 1 0 1 1 1 0 1 0 1 1 0 1 1 1 1 1 1 0 1 1 0 0 0 1 0 1 1
 0 0 1 0 1 1 1 0 1 0 1 1 1 0 1 0 1 1 0 0 0 0 1 1 1 1 0 0 0 1 1 0 1 1 1 1 1
 0 1 0 0 1 1 1 0 1 1 1 1 1 0 0 0 1 1 1 0 1 0 0 1 0 1 1 1 1 1 1 0 1 1 0 1 0
 0 1 0 1 1 1 0 1 1 0 0 0 0 0 0 1 0 1 0 1 0 1 0 1 1 1 0 0 0 0 1 0 0 0 1 1 1
 0 1 1 1 1 0 1 0 1 1 0 1 0 0 0 0 1 0 0 0 1 1 1 1 0 0 0 1 1 0 1 1 0 0 1 0 1
 1 0 0 1 0 1 1 1 0 1 0 0 1 0 0 1 1 1 1 1 1 0 1 1 1 0 1 0 1 0 1 1 0 0 0 1 1
 1 0 1 1 1 1 1 1 1 0 0 1 1 1 1 1 0 1 1 0 1 0 1 0 0 1 0 0 1 1 0 0 1 1 0 1 0
 0 0 0 1 0 1 1 1 1 0 1 0 1 0 0 1 1 0 1 1 0 1 1 0 1 1 1 0 0 1 0 1 1 0 1 0 0
 1 0 1 0 1 0 0 0 0 0 0 1 1 1 1 1 1 1 0 1 1 1 1 0 0 1 0 0]
```

[17]:
```
#Evaluate the classifier
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(y_test, y_pred_knn))
print(classification_report(y_test, y_pred_knn))
```

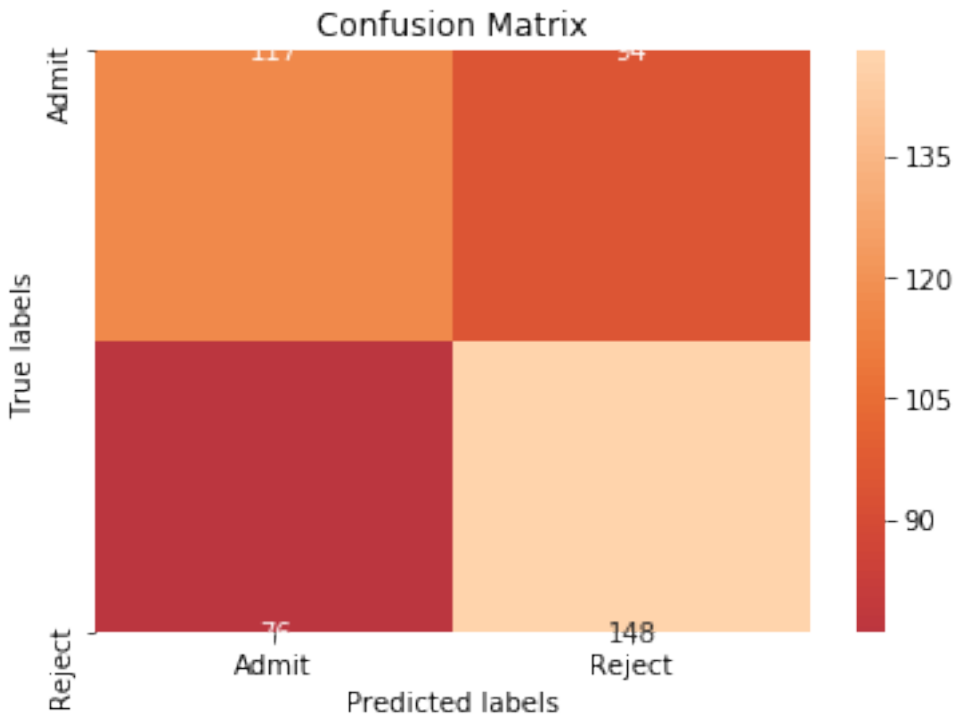
```
[[127  84]
 [ 76 148]]
              precision    recall  f1-score   support

           0       0.63      0.60      0.61       211
           1       0.64      0.66      0.65       224

    accuracy                           0.63       435
   macro avg       0.63      0.63      0.63       435
weighted avg       0.63      0.63      0.63       435
```

[18]:
```
from sklearn.metrics import confusion_matrix, f1_score,␣
 ↪accuracy_score,precision_score,recall_score
print("Accuracy Score = ",accuracy_score(y_test_label, y_pred_knn))
print("precision_score: ", precision_score(y_test_label,knnc.predict(x_test)))
print("recall_score: ", recall_score(y_test_label,knnc.predict(x_test)))
print("f1_score: ",f1_score(y_test_label,knnc.predict(x_test)))
```

```
Accuracy Score =  0.632183908045977
precision_score:  0.6379310344827587
recall_score:  0.6607142857142857
f1_score:  0.6491228070175439
```

[35]:
```
#plot the confusion matrix
conf_matrix= plt.subplot()
labels=[0, 1]
cm = confusion_matrix(y_test, y_pred_knn)
print(y_test)

columns=['Admit', 'Reject']
index=['Admit', 'Reject']
cm_df = pd.DataFrame(cm,columns,index)
sns.heatmap(cm_df, annot=True,ax=conf_matrix, fmt='g', center=True);␣
 ↪#annot=True to annotate cells
conf_matrix.set_xlabel('Predicted labels');conf_matrix.set_ylabel('True␣
 ↪labels');
conf_matrix.set_title('Confusion Matrix');
conf_matrix.xaxis.set_ticklabels(['Admit', 'Reject']); conf_matrix.yaxis.
 ↪set_ticklabels(['Admit', 'Reject']);


#print("Confusion Matrix: \n", confusion_matrix(y_test, y_pred))
print ("Accuracy : ", accuracy_score(y_test,y_pred_knn)*100)
```

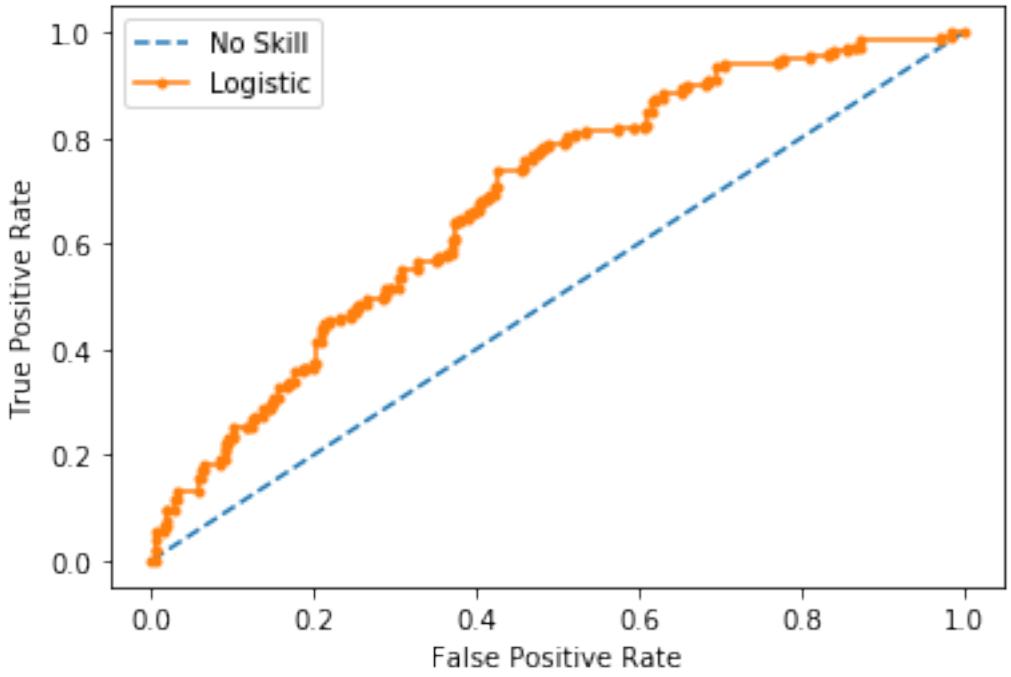
```
[1 0 0 1 0 0 0 0 1 1 1 0 1 0 1 1 0 0 1 1 1 0 0 1 1 0 1 0 0 0 0 0 1 0 0 0 1
 1 0 0 0 0 1 1 1 0 1 1 1 0 1 0 0 1 0 0 1 0 1 1 1 0 0 0 1 0 1 0 1 1 1 1 0 1
 1 0 1 1 1 0 0 1 1 1 1 0 1 1 1 1 0 1 0 0 0 1 1 0 0 0 0 0 0 0 0 1 1 1 0 0 1
 1 0 1 0 1 0 0 0 0 0 0 1 0 0 1 0 1 1 1 1 1 1 1 1 0 1 0 0 1 1 1 0 1 1 0 1 1
 0 1 0 1 1 0 0 0 0 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0 0 0 0 0 1 1 0 1 1 1 1 0
 1 1 0 1 0 1 1 1 0 1 1 0 0 0 0 0 0 0 1 1 0 0 1 1 0 0 1 1 1 1 0 0 1 1 1 0 1
 1 1 1 1 1 1 1 0 1 1 0 1 1 0 0 1 0 1 0 1 0 1 0 0 1 0 1 0 0 1 1 1 0 1 0 1 0
 1 0 1 1 1 0 0 0 1 0 1 1 1 0 0 1 1 1 0 0 1 1 1 1 1 0 1 1 1 0 0 1 1 1 1 0 1
 1 1 0 1 0 1 0 1 0 1 0 0 1 1 0 1 0 0 0 1 1 1 0 0 1 1 1 1 0 0 0 0 1 0 1 1 1
 0 0 0 1 1 0 1 1 0 0 0 1 1 1 0 1 1 1 1 0 1 0 0 1 1 0 0 0 1 0 0 0 1 1 0 1 0
 0 0 1 0 0 1 0 1 1 0 1 0 1 1 0 0 0 1 0 0 0 1 0 1 1 1 1 0 0 1 0 0 1 0 0 1 0
 0 0 1 0 0 0 0 1 0 1 0 1 1 0 0 1 1 0 1 1 0 1 1 1 1 0 1 0]
Accuracy :  60.91954022988506
```



[19]:
```
# roc curve and auc


#lr_probs = model.predict_proba(testX)
lr_probs=model.predict_proba(x_test)
# keep probabilities for the positive outcome only
lr_probs = lr_probs[:, 1]
# calculate scores
ns_auc = roc_auc_score(y_test, ns_probs)
lr_auc = roc_auc_score(y_test, lr_probs)
# summarize scores
print('No Skill: ROC AUC=%.3f' % (ns_auc))
print('Logistic: ROC AUC=%.3f' % (lr_auc))
# calculate roc curves
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)
lr_fpr, lr_tpr, _ = roc_curve(y_test, lr_probs)
# plot the roc curve for the model
pyplot.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
pyplot.plot(lr_fpr, lr_tpr, marker='.', label='Logistic')
# axis labels
pyplot.xlabel('False Positive Rate')
pyplot.ylabel('True Positive Rate')
# show the legend
```

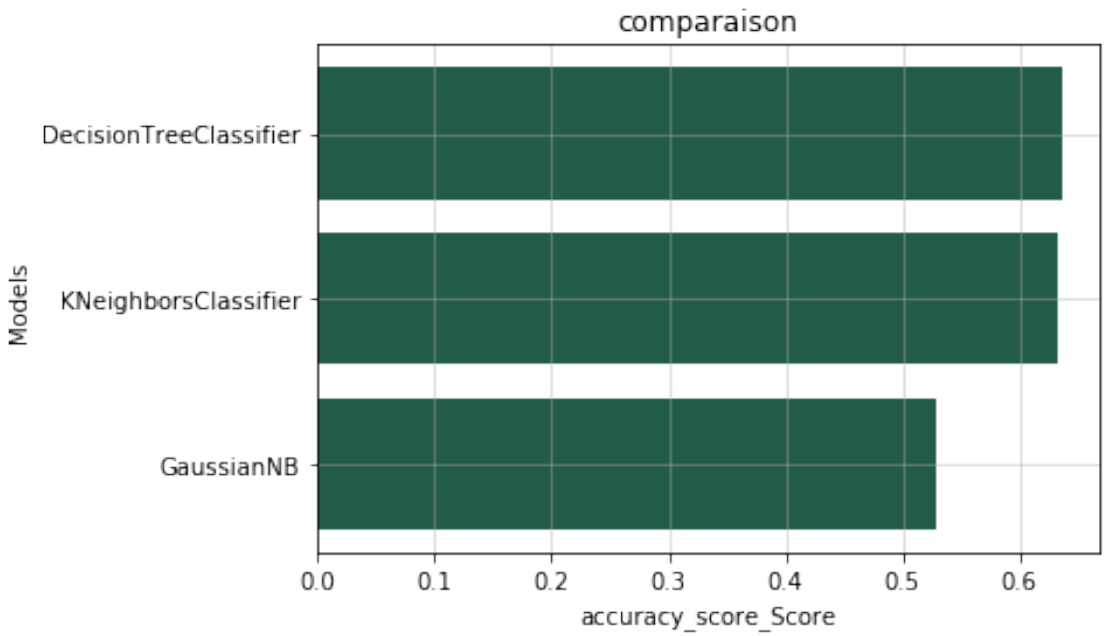
```
pyplot.legend()
# show the plot
pyplot.show()
```

```
No Skill: ROC AUC=0.500
Logistic: ROC AUC=0.683
```



[20]:
```
#the accuracy fromDecisionTreeClassifier
DecisionTreeClassifierAccuracy=0.63678160919540225
```

[21]:
```
#Comaparaison between the three classifier
x = ["GaussianNB","KNeighborsClassifier","DecisionTreeClassifier"]
y = np.array([accuracy_score(target_test, predicted),accuracy_score(y_test,␣
 ↪y_pred_knn),DecisionTreeClassifierAccuracy])
plt.barh(x,y, color='#225b46')
plt.xlabel("accuracy_score_Score")
plt.ylabel("Models")
plt.title("comparaison")
plt.grid(alpha=0.5)
plt.show()
```


comparaison
DecisionTreeClassifier
KNeighborsClassifier
GaussianNB
Models
0.0
0.1
0.2
0.3
0.4
0.5
0.6
accuracy_score_Score

[ ]: