Modelos - SIN BALANCEAR

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1 MODELOS DE MACHINE LEARNING

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Importar librerias

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

1.1 Conjunto con Datos método Sin Balancear

Importar el data de entrenamientos (sin balancear) y data test

Cargar conjuntos de entrenamiento balanceados (4 métodos) y conjunto de test. (los conjuntos de entrenamiento y test fueron dividimos en 80% y 20%)

[3]:
```
#data entrenamiento balanceado con ROSE-OVER
data_train_bal = pd.read_csv('Data_train.csv', encoding='latin-1',sep=';')
# 80% sin balancear
```

[4]:
```
#data test
data_test = pd.read_csv('Data_test.csv',encoding='latin-1',sep=';')
# 20% de la data completa
```

[5]:
```
X_train=data_train_bal.iloc[:,1:23].values
y_train=data_train_bal.iloc[:,0].values
X_test=data_test.iloc[:,1:23].values
y_test=data_test.iloc[:,0].values
```

1.2 Ajustar el clasificador Random Forest en el Conjunto de Entrenamiento

[6]:
```
#Validación cruzada (datos)
from sklearn.model_selection import KFold, cross_val_score
from sklearn.ensemble import RandomForestClassifier
kf =KFold(n_splits=5, shuffle=True, random_state=42)
```

```python
score = cross_val_score(RandomForestClassifier(n_estimators = 100, n_jobs=2,␣
↪criterion = "entropy", random_state = 123), X_train, y_train, cv= kf,␣
↪scoring="accuracy")
print(f'Scores for each fold are: {score}')
print(f'Average score: {"{:.4f}".format(score.mean())}')
```

```
Scores for each fold are: [0.7307474  0.72511826 0.73278146 0.73570178
0.72907895]
Average score: 0.7307
```

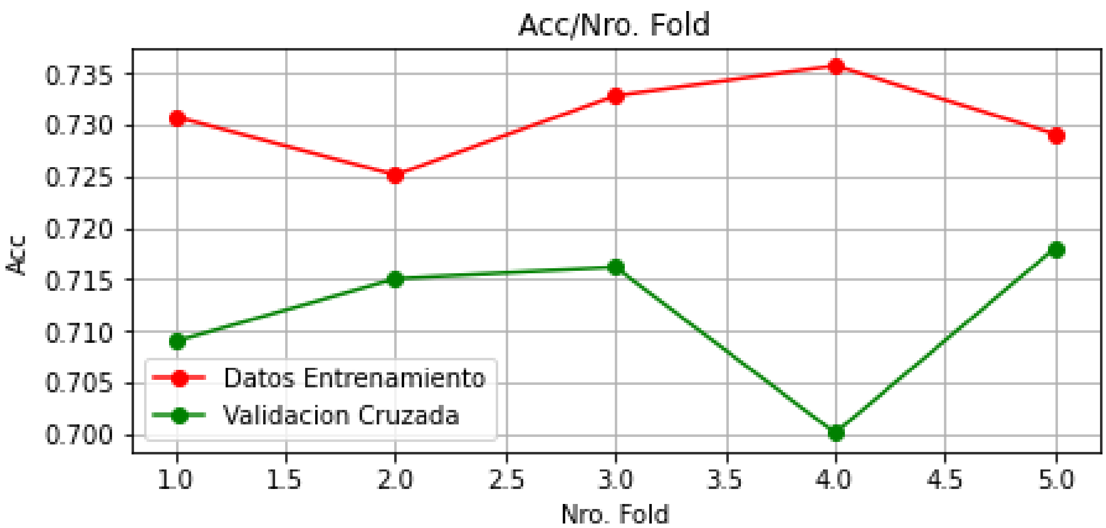
[7]:
```python
#Validación cruzada (gráfico y datos)
def graficar_Accu_scores(estimator, X_train,␣
↪y_train,X_test,y_test,nparts=5,jobs=None):
    kf = KFold(n_splits=nparts,shuffle=True, random_state=42)
    fig,axes = plt.subplots(figsize=(7, 3))
    axes.set_title("Acc/Nro. Fold")
    axes.set_xlabel("Nro. Fold")
    axes.set_ylabel("Acc")
    train_scores = cross_val_score(estimator, X_train, y_train, cv = kf,␣
↪n_jobs=jobs,scoring="accuracy")
    test_scores = cross_val_score(estimator, X_test,y_test, cv = kf,␣
↪n_jobs=jobs,scoring="accuracy")
    train_sizes = range(1,nparts+1,1)
    axes.grid()
    axes.plot(train_sizes, train_scores, 'o-', color="r",label="Datos␣
↪Entrenamiento")
    axes.plot(train_sizes, test_scores, 'o-', color="g",label="Validacion␣
↪Cruzada")
    axes.legend(loc="best")
    return train_scores
```

[8]:
```python
from sklearn.ensemble import RandomForestClassifier
clas_rndforest = RandomForestClassifier(n_estimators = 100, n_jobs=2, criterion␣
↪= "entropy", random_state = 123)
clas_rndforest.fit(X_train, y_train)
```

[8]:
```
RandomForestClassifier(criterion='entropy', n_jobs=2, random_state=123)
```

[9]:
```python
#Validación cruzada (gráfico y datos)
graficar_Accu_scores(clas_rndforest,X_train,y_train,X_test,y_test,nparts=5,jobs=2)
```

[9]:
```
array([0.7307474 , 0.72511826, 0.73278146, 0.73570178, 0.72907895])
```



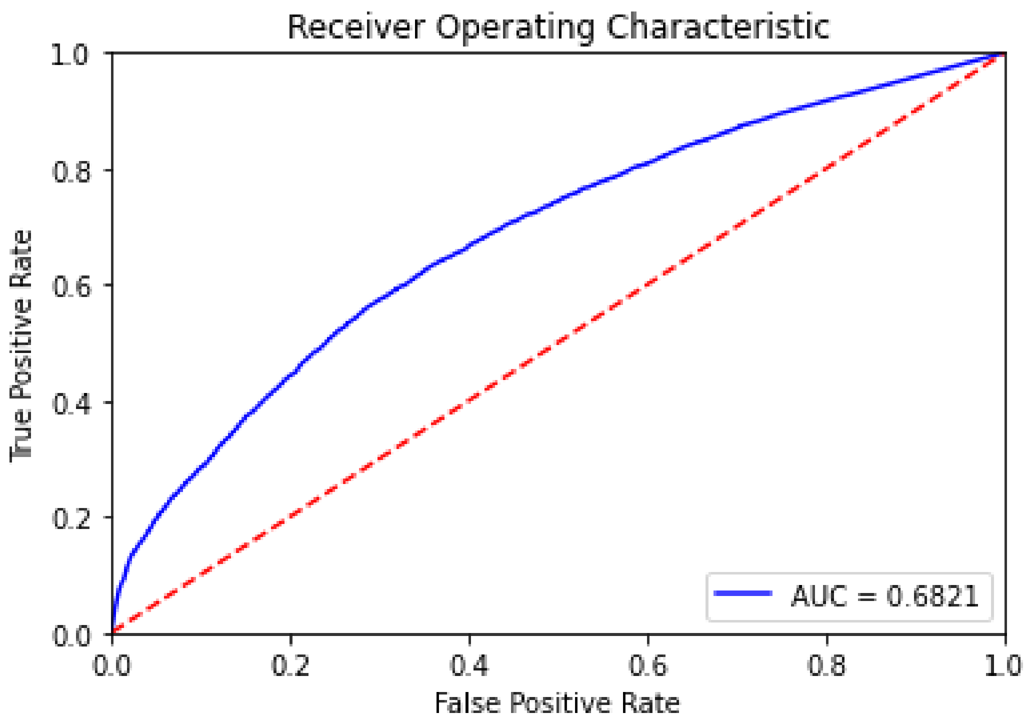
1.2.1 Predicción resultados

[10]:
```
y_pred  = clas_rndforest.predict(X_test)
##matriz de confusión
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
display(confusion_matrix(y_test, y_pred))
class_report=classification_report(y_test, y_pred)
print(class_report)
```

```
array([[17087,  2162],
       [ 4997,  2178]], dtype=int64)

              precision    recall  f1-score   support

           0       0.77      0.89      0.83     19249
           1       0.50      0.30      0.38      7175

    accuracy                           0.73     26424
   macro avg       0.64      0.60      0.60     26424
weighted avg       0.70      0.73      0.71     26424
```

[11]:
```
#Curvas ROC
import sklearn.metrics as metrics
# calcular fpr y tpr para todos los thresholds de la clasificación
probs = clas_rndforest.predict_proba(X_test)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_test, preds)
```

```
roc_auc = metrics.auc(fpr, tpr)

# method I: plt
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.4f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



1.3 Ajustar el clasificador NAIVE BAYES en el Conjunto de Entrenamiento

[12]:
```
#validación cruzada (datos)
from sklearn.model_selection import KFold, cross_val_score
from sklearn.naive_bayes import GaussianNB
kf =KFold(n_splits=5, shuffle=True, random_state=42)
score = cross_val_score(GaussianNB(), X_train, y_train, cv= kf,␣
 ↪scoring="accuracy")
print(f'Scores for each fold are: {score}')
```

```
print(f'Average score: {"{:.4f}".format(score.mean())}')
```

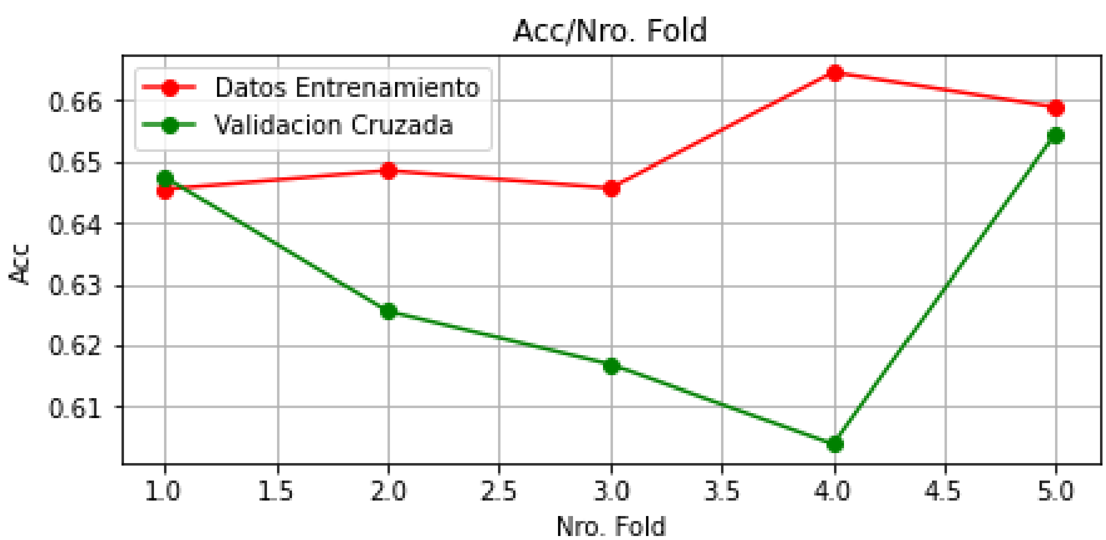
```
Scores for each fold are: [0.64550615 0.64858089 0.64569536 0.66464828
0.65892426]
Average score: 0.6527
```

[6]:
```
from sklearn.naive_bayes import GaussianNB
class_nb = GaussianNB()
class_nb.fit(X_train, y_train)
```

[6]:
```
GaussianNB()
```

[14]:
```
#Validación cruzada
graficar_Accu_scores(class_nb,X_train,y_train,X_test,y_test,nparts=5,jobs=2)
```

[14]:
```
array([0.64550615, 0.64858089, 0.64569536, 0.66464828, 0.65892426])
```



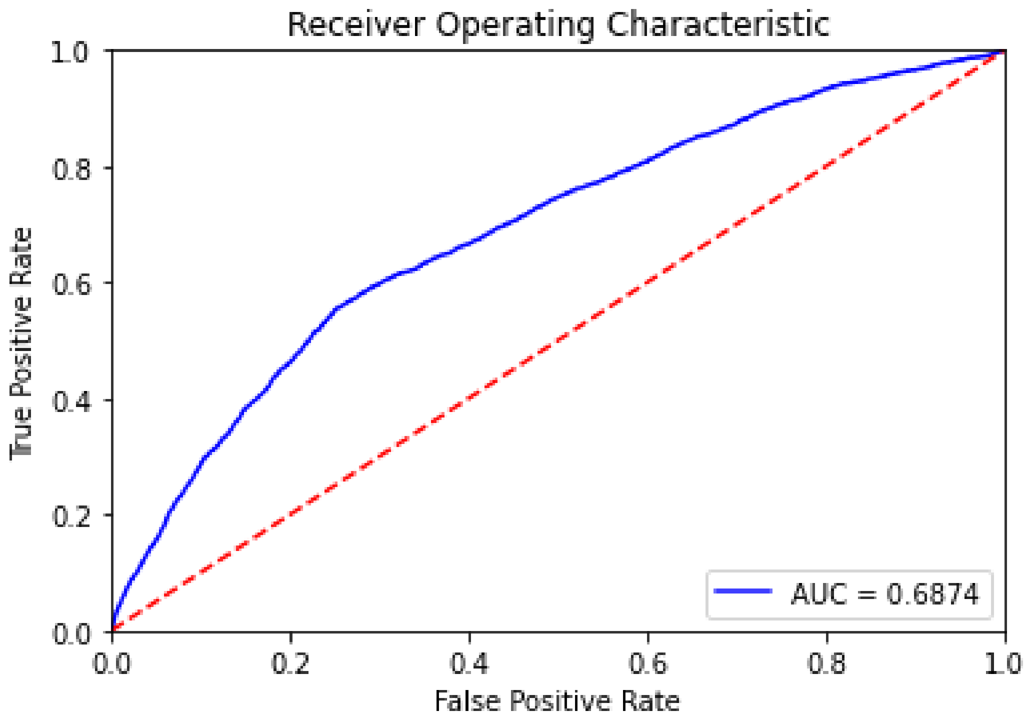
[8]:
```
# Predecir los resultados
y_pred_nb  = class_nb.predict(X_test)
# Matriz de confusión
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
#cm_nb = confusion_matrix(y_test, y_pred_nb)
display(confusion_matrix(y_test, y_pred_nb))
class_report=classification_report(y_test, y_pred_nb)
print(class_report)
```

```
array([[12742,  6507],
       [ 2711,  4464]], dtype=int64)
```

```
              precision    recall  f1-score   support

           0       0.82      0.66      0.73     19249
           1       0.41      0.62      0.49      7175

    accuracy                           0.65     26424
   macro avg       0.62      0.64      0.61     26424
weighted avg       0.71      0.65      0.67     26424
```

[16]:

```python
#Curvas ROC
import sklearn.metrics as metrics
# calcular fpr y tpr para todos los thresholds de la clasificación
probs = class_nb.predict_proba(X_test)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_test, preds)
roc_auc1 = metrics.auc(fpr, tpr)

# method I: plt
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.4f' % roc_auc1)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



1.4 Ajustar el clasificador REDES NEURONALES en el Conjunto de Entrenamiento

[17]:
```
import keras
from keras.models import Sequential
from keras.layers import Dense
```

[18]:
```
#validación cruzada (datos)
import keras
from keras.wrappers.scikit_learn import KerasClassifier
from keras.models import Sequential
from keras.layers import Dense
from sklearn.model_selection import KFold, cross_val_score

def built_class_RN():
    #Inicializar la RNA
    class_RN = Sequential()
    #Añadir las capas de entrada y primera capa oculta
    class_RN.add(Dense(units = 12, kernel_initializer = "uniform", activation =␣
 ↪"relu", input_dim = 23))
    #Añadir la segunda capa oculta
    class_RN.add(Dense(units = 10, kernel_initializer = "uniform",  activation␣
 ↪= "relu"))
```

```
    #Añadir la capa de salida
    class_RN.add(Dense(units = 1, kernel_initializer = "uniform",  activation =␣
 ↪"sigmoid"))
    #Compilar la RNA
    class_RN.compile(optimizer = "adam", loss = "binary_crossentropy", metrics␣
 ↪= ["accuracy"])
    return class_RN

#Ajustar la RNA al Conjunto de Entrenamiento
class_RN = KerasClassifier(build_fn=built_class_RN, batch_size = 10, epochs =␣
 ↪100)
kf =KFold(n_splits=5, shuffle=True, random_state=42)
Accuracy = cross_val_score(class_RN, X_train, y_train, cv= kf, n_jobs=-1)
```

```
C:\Users\jenny\AppData\Local\Temp/ipykernel_11812/2278733859.py:22:
DeprecationWarning: KerasClassifier is deprecated, use Sci-Keras
(https://github.com/adriangb/scikeras) instead.
  class_RN = KerasClassifier(build_fn=built_class_RN, batch_size = 10, epochs =
100)
```

[19]:
```
print(f'Scores for each fold are: {Accuracy}')
print(f'Average score: {"{:.4f}".format(Accuracy.mean())}')
```

```
Scores for each fold are: [0.76087987 0.76310313 0.76073796 0.76597756
0.75949669]
Average score: 0.7620
```

[11]:
```
#Inicializar la RNA
class_RN = Sequential()
#Añadir las capas de entrada y primera capa oculta
class_RN.add(Dense(units = 12, kernel_initializer = "uniform",
                     activation = "relu", input_dim = 23))
#Añadir la segunda capa oculta
class_RN.add(Dense(units = 10, kernel_initializer = "uniform",  activation =␣
 ↪"relu"))
#Añadir la capa de salida
class_RN.add(Dense(units = 1, kernel_initializer = "uniform",  activation =␣
 ↪"sigmoid"))
#Compilar la RNA
class_RN.compile(optimizer = "adam", loss = "binary_crossentropy", metrics =␣
 ↪["accuracy"])
#Ajustar la RNA al Conjunto de Entrenamiento
class_RN.fit(X_train, y_train,  batch_size = 10, epochs = 100)
```

```
Epoch 1/100
10570/10570 [==============================] - 23s 2ms/step - loss: 0.5256 -
accuracy: 0.7405
Epoch 2/100
```

```
10570/10570 [==============================] - 18s 2ms/step - loss: 0.5213 -
accuracy: 0.7442
Epoch 3/100
10570/10570 [==============================] - 10s 968us/step - loss: 0.5204 -
accuracy: 0.7452
Epoch 4/100
10570/10570 [==============================] - 10s 919us/step - loss: 0.5200 -
accuracy: 0.7454
Epoch 5/100
10570/10570 [==============================] - 12s 1ms/step - loss: 0.5194 -
accuracy: 0.7458
Epoch 6/100
10570/10570 [==============================] - 12s 1ms/step - loss: 0.5191 -
accuracy: 0.7459
Epoch 7/100
10570/10570 [==============================] - 12s 1ms/step - loss: 0.5186 -
accuracy: 0.7468
Epoch 8/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5179 -
accuracy: 0.7468
Epoch 9/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5170 -
accuracy: 0.7483
Epoch 10/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5154 -
accuracy: 0.7510
Epoch 11/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5143 -
accuracy: 0.7532
Epoch 12/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5135 -
accuracy: 0.7550
Epoch 13/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5127 -
accuracy: 0.7558
Epoch 14/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5121 -
accuracy: 0.7564
Epoch 15/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5116 -
accuracy: 0.7575
Epoch 16/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5114 -
accuracy: 0.7579
Epoch 17/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5110 -
accuracy: 0.7586
Epoch 18/100
```

```
10570/10570 [==============================] - 10s 959us/step - loss: 0.5105 -
accuracy: 0.7588
Epoch 19/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5103 -
accuracy: 0.7587
Epoch 20/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5103 -
accuracy: 0.7591
Epoch 21/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5098 -
accuracy: 0.7595
Epoch 22/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5098 -
accuracy: 0.7598
Epoch 23/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5095 -
accuracy: 0.7597
Epoch 24/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5096 -
accuracy: 0.7594
Epoch 25/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5093 -
accuracy: 0.7593
Epoch 26/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5093 -
accuracy: 0.7601
Epoch 27/100
10570/10570 [==============================] - 11s 993us/step - loss: 0.5091 -
accuracy: 0.7601
Epoch 28/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5092 -
accuracy: 0.7598
Epoch 29/100
10570/10570 [==============================] - 12s 1ms/step - loss: 0.5088 -
accuracy: 0.7605
Epoch 30/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5088 -
accuracy: 0.7604
Epoch 31/100
10570/10570 [==============================] - 12s 1ms/step - loss: 0.5087 -
accuracy: 0.7601
Epoch 32/100
10570/10570 [==============================] - 12s 1ms/step - loss: 0.5085 -
accuracy: 0.7602
Epoch 33/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5085 -
accuracy: 0.7600
Epoch 34/100
```

```
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5085 -
accuracy: 0.7610
Epoch 35/100
10570/10570 [==============================] - 11s 993us/step - loss: 0.5083 -
accuracy: 0.7613
Epoch 36/100
10570/10570 [==============================] - 10s 939us/step - loss: 0.5084 -
accuracy: 0.7603
Epoch 37/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5081 -
accuracy: 0.7610
Epoch 38/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5083 -
accuracy: 0.7607
Epoch 39/100
10570/10570 [==============================] - 10s 987us/step - loss: 0.5080 -
accuracy: 0.7609
Epoch 40/100
10570/10570 [==============================] - 12s 1ms/step - loss: 0.5080 -
accuracy: 0.7607
Epoch 41/100
10570/10570 [==============================] - 10s 982us/step - loss: 0.5076 -
accuracy: 0.7618
Epoch 42/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5077 -
accuracy: 0.7612
Epoch 43/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5075 -
accuracy: 0.7621
Epoch 44/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5076 -
accuracy: 0.7616
Epoch 45/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5075 -
accuracy: 0.7620
Epoch 46/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5073 -
accuracy: 0.7619
Epoch 47/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5074 -
accuracy: 0.7620
Epoch 48/100
10570/10570 [==============================] - 10s 991us/step - loss: 0.5074 -
accuracy: 0.7612
Epoch 49/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5071 -
accuracy: 0.7620
Epoch 50/100
```

```
10570/10570 [==============================] - 11s 999us/step - loss: 0.5071 -
accuracy: 0.7616
Epoch 51/100
10570/10570 [==============================] - 11s 999us/step - loss: 0.5069 -
accuracy: 0.7619
Epoch 52/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5070 -
accuracy: 0.7617
Epoch 53/100
10570/10570 [==============================] - 10s 966us/step - loss: 0.5070 -
accuracy: 0.7617
Epoch 54/100
10570/10570 [==============================] - 10s 941us/step - loss: 0.5070 -
accuracy: 0.7620
Epoch 55/100
10570/10570 [==============================] - 10s 945us/step - loss: 0.5068 -
accuracy: 0.7620
Epoch 56/100
10570/10570 [==============================] - 11s 997us/step - loss: 0.5068 -
accuracy: 0.7626
Epoch 57/100
10570/10570 [==============================] - 10s 986us/step - loss: 0.5066 -
accuracy: 0.7624
Epoch 58/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5066 -
accuracy: 0.7626
Epoch 59/100
10570/10570 [==============================] - 10s 974us/step - loss: 0.5065 -
accuracy: 0.7621
Epoch 60/100
10570/10570 [==============================] - 10s 960us/step - loss: 0.5064 -
accuracy: 0.7624
Epoch 61/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5063 -
accuracy: 0.7628
Epoch 62/100
10570/10570 [==============================] - 10s 973us/step - loss: 0.5062 -
accuracy: 0.7619
Epoch 63/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5059 -
accuracy: 0.7629
Epoch 64/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5062 -
accuracy: 0.7624
Epoch 65/100
10570/10570 [==============================] - 10s 990us/step - loss: 0.5059 -
accuracy: 0.7635
Epoch 66/100
```

```
10570/10570 [==============================] - 10s 988us/step - loss: 0.5059 -
accuracy: 0.7635
Epoch 67/100
10570/10570 [==============================] - 10s 963us/step - loss: 0.5059 -
accuracy: 0.7637
Epoch 68/100
10570/10570 [==============================] - 11s 996us/step - loss: 0.5058 -
accuracy: 0.7637
Epoch 69/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5060 -
accuracy: 0.7633
Epoch 70/100
10570/10570 [==============================] - 10s 987us/step - loss: 0.5056 -
accuracy: 0.7636
Epoch 71/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5059 -
accuracy: 0.7629
Epoch 72/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5055 -
accuracy: 0.7633
Epoch 73/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5057 -
accuracy: 0.7632
Epoch 74/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5055 -
accuracy: 0.7624
Epoch 75/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5054 -
accuracy: 0.7636
Epoch 76/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5055 -
accuracy: 0.7635
Epoch 77/100
10570/10570 [==============================] - 10s 956us/step - loss: 0.5056 -
accuracy: 0.7632
Epoch 78/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5054 -
accuracy: 0.7635
Epoch 79/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5054 -
accuracy: 0.7625
Epoch 80/100
10570/10570 [==============================] - 10s 976us/step - loss: 0.5053 -
accuracy: 0.7640
Epoch 81/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5053 -
accuracy: 0.7625
Epoch 82/100
```

```
10570/10570 [==============================] - 10s 964us/step - loss: 0.5052 -
accuracy: 0.7637
Epoch 83/100
10570/10570 [==============================] - 10s 958us/step - loss: 0.5051 -
accuracy: 0.7643
Epoch 84/100
10570/10570 [==============================] - 11s 993us/step - loss: 0.5054 -
accuracy: 0.7639
Epoch 85/100
10570/10570 [==============================] - 10s 963us/step - loss: 0.5052 -
accuracy: 0.7630
Epoch 86/100
10570/10570 [==============================] - 12s 1ms/step - loss: 0.5049 -
accuracy: 0.7643
Epoch 87/100
10570/10570 [==============================] - 12s 1ms/step - loss: 0.5052 -
accuracy: 0.7629
Epoch 88/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5051 -
accuracy: 0.7639
Epoch 89/100
10570/10570 [==============================] - 10s 986us/step - loss: 0.5049 -
accuracy: 0.7632
Epoch 90/100
10570/10570 [==============================] - 10s 970us/step - loss: 0.5050 -
accuracy: 0.7637
Epoch 91/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5050 -
accuracy: 0.7640
Epoch 92/100
10570/10570 [==============================] - 10s 974us/step - loss: 0.5050 -
accuracy: 0.7642
Epoch 93/100
10570/10570 [==============================] - 10s 977us/step - loss: 0.5049 -
accuracy: 0.7641
Epoch 94/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5049 -
accuracy: 0.7634
Epoch 95/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5047 -
accuracy: 0.7641
Epoch 96/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5047 -
accuracy: 0.7635
Epoch 97/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5046 -
accuracy: 0.7636
Epoch 98/100
```

```
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5050 -
accuracy: 0.7636
Epoch 99/100
10570/10570 [==============================] - 11s 1ms/step - loss: 0.5046 -
accuracy: 0.7631
Epoch 100/100
10570/10570 [==============================] - 10s 985us/step - loss: 0.5048 -
accuracy: 0.7639
```

[11]: <keras.callbacks.History at 0x2002ea3ac70>

[12]:
```
test_loss, test_acc = class_RN.evaluate(X_test,  y_test, verbose=2)
print('\nTest Accuracy:', test_acc)
```

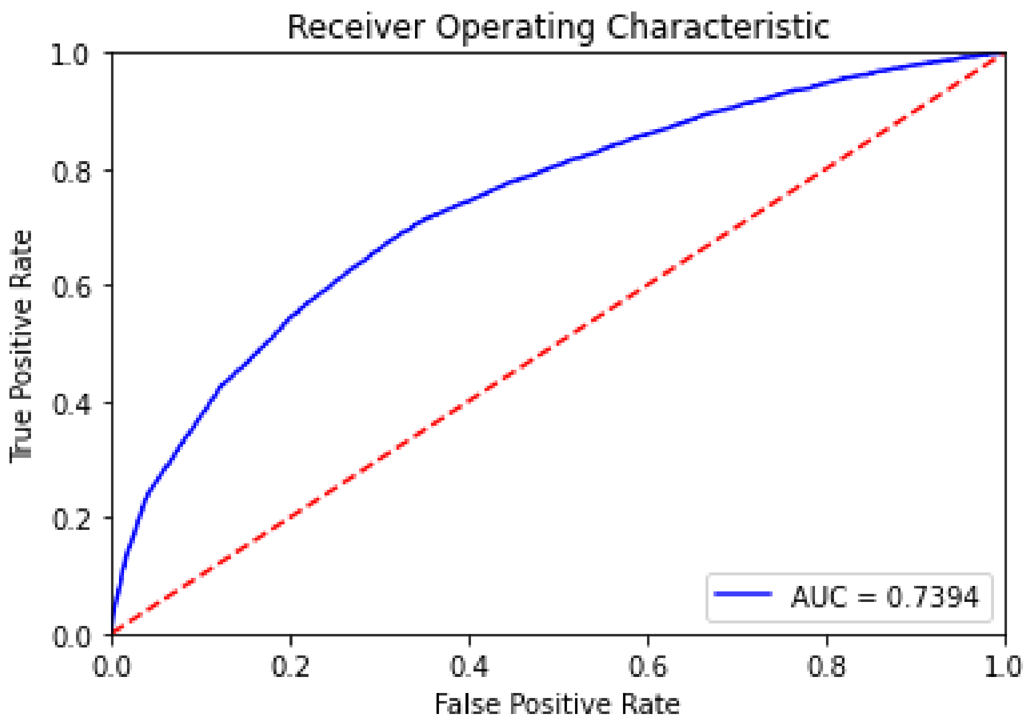
```
826/826 - 1s - loss: 0.5104 - accuracy: 0.7604 - 701ms/epoch - 848us/step

Test Accuracy: 0.7604072093963623
```

[13]:
```
# Evaluar el modelo y calcular predicciones finales
# Predicción de los resultados con el Conjunto de Testing
y_pred_rn  = class_RN.predict(X_test)
y_pred_rn = (y_pred_rn>0.5)
#Elaborar una matriz de confusión
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
display(confusion_matrix(y_test, y_pred_rn))
class_report=classification_report(y_test, y_pred_rn)
print(class_report)
```

```
array([[18416,   833],
       [ 5498,  1677]], dtype=int64)
              precision    recall  f1-score   support

           0       0.77      0.96      0.85     19249
           1       0.67      0.23      0.35      7175

    accuracy                           0.76     26424
   macro avg       0.72      0.60      0.60     26424
weighted avg       0.74      0.76      0.72     26424
```

[23]:
```
#Curva ROC
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
y_pred_rn_curv = class_RN.predict(X_test).ravel()

nn_fpr_keras, nn_tpr_keras, nn_thresholds_keras = roc_curve(y_test,
 ↪y_pred_rn_curv)
```

```
auc_keras = auc(nn_fpr_keras, nn_tpr_keras)
# method I: plt
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(nn_fpr_keras, nn_tpr_keras, 'b', label = 'AUC = %0.4f' % auc_keras)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



1.5 Ajustar el clasificador SVM en el Conjunto de Entrenamiento

[24]:
```
#validación cruzada (datos)
from sklearn.model_selection import KFold, cross_val_score
from sklearn.svm import SVC
kf =KFold(n_splits=5, shuffle=True, random_state=42)
score = cross_val_score(SVC(kernel='rbf',random_state=123), X_train, y_train,␣
 ↪cv= kf, scoring="accuracy")
print(f'Scores for each fold are: {score}')
print(f'Average score: {"{:.4f}".format(score.mean())}')
```

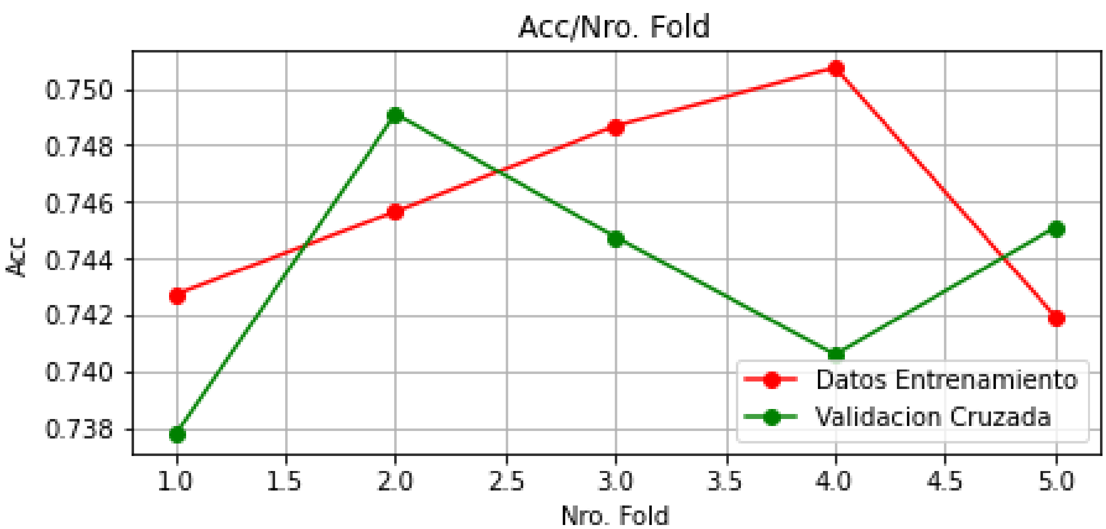
```
Scores for each fold are: [0.74271523 0.74564806 0.7486755  0.75074507
0.74194617]
Average score: 0.7459
```

[26]:
```python
# Fitting SVM to the Training set using Kernel as rbf.
from sklearn.svm import SVC
class_svm = SVC(kernel='rbf',probability=True,random_state=123)
class_svm.fit(X_train, y_train)
```

[26]:
```
SVC(probability=True, random_state=123)
```

[27]:
```python
#Validación cruzada (gráfico y datos)
graficar_Accu_scores(class_svm,X_train,y_train,X_test,y_test,nparts=5,jobs=2)
```

[27]:
```
array([0.74271523, 0.74564806, 0.7486755 , 0.75074507, 0.74194617])
```

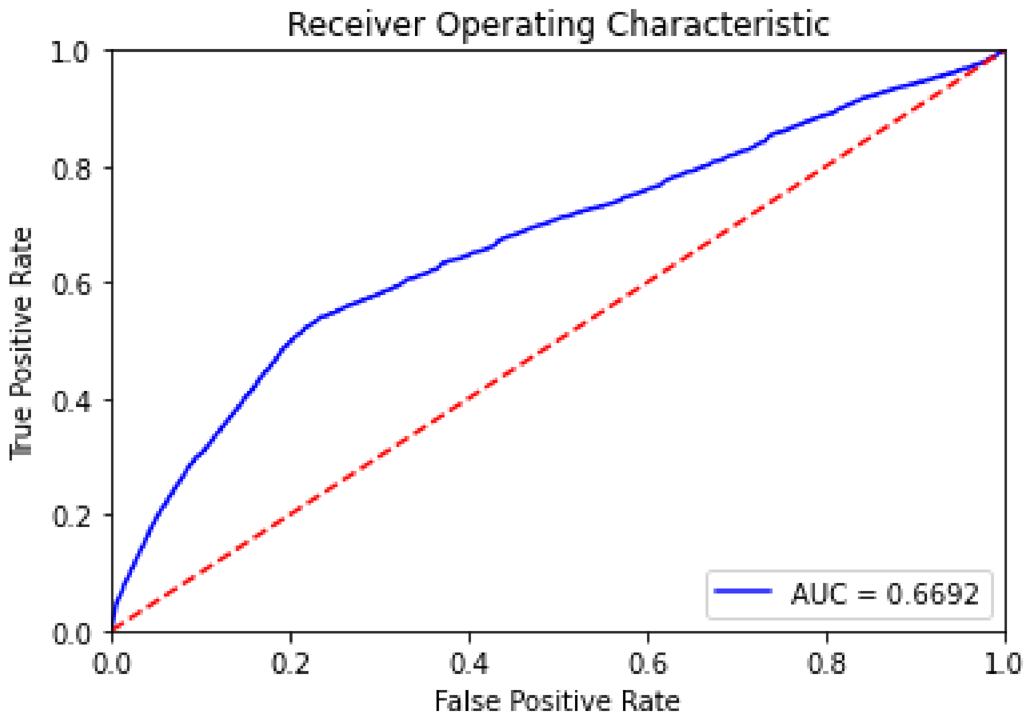


[28]:
```python
#Predicción resultados
y_pred_svm  = class_svm.predict(X_test)
##matriz de confusión
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
display(confusion_matrix(y_test, y_pred_svm))
class_report=classification_report(y_test, y_pred_svm)
print(class_report)
```

```
array([[17953,  1296],
       [ 5490,  1685]], dtype=int64)

              precision    recall  f1-score   support
```

```
              0       0.77      0.93      0.84     19249
              1       0.57      0.23      0.33      7175

       accuracy                           0.74     26424
      macro avg       0.67      0.58      0.59     26424
   weighted avg       0.71      0.74      0.70     26424
```

[29]:
```python
#Curvas ROC
import sklearn.metrics as metrics
# calcular fpr y tpr para todos los thresholds de la clasificación
probs = class_svm.predict_proba(X_test)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_test, preds)
roc_auc = metrics.auc(fpr, tpr)

# method I: plt
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.4f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```


Receiver Operating Characteristic
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
AUC = 0.6692