Modelos - ROSE-OVER

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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 balanceados método ROSE - OVER

Importar el data de entrenamiento (balanceados) 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%)

[2]:
```
#data entrenamiento balanceado con ROSE-OVER
data_train_bal = pd.read_csv('Data_train_Rose_Over_ c.csv',␣
 ↪encoding='latin-1',sep=';')
# 80% de la data completa
```

[3]:
```
#data test
data_test = pd.read_csv('Data_test.csv',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

[11]:
```
#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)
```

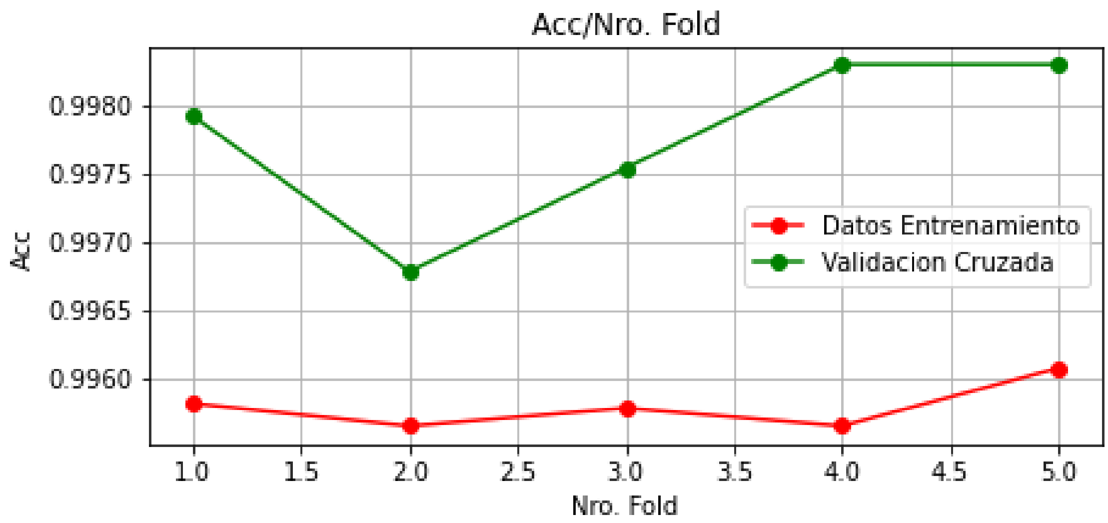
```
score = cross_val_score(RandomForestClassifier(n_estimators = 100, n_jobs=2,␣
↪criterion = "entropy", random_state = 123), X_train, y_train, cv= kf,␣
↪scoring="accuracy")
print(f'Scores for each fold are: {score}')
print(f'Average score: {"{:.4f}".format(score.mean())}')
```

```
Scores for each fold are: [0.9958159  0.99565358 0.99578333 0.99565358
0.99607525]
Average score: 0.9958
```

[12]:
```
#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
```

[13]:
```
#Validación cruzada (gráfico y datos)
graficar_Accu_scores(clas_rndforest,X_train,y_train,X_test,y_test,nparts=5,jobs=2)
```

[13]:
```
array([0.9958159 , 0.99565358, 0.99578333, 0.99565358, 0.99607525])
```



[6]:
```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)
```

[6]:
```
RandomForestClassifier(criterion='entropy', n_jobs=2, random_state=123)
```

1.2.1 Predicción resultados

[8]:
```python
y_pred  = clas_rndforest.predict(X_test)
```

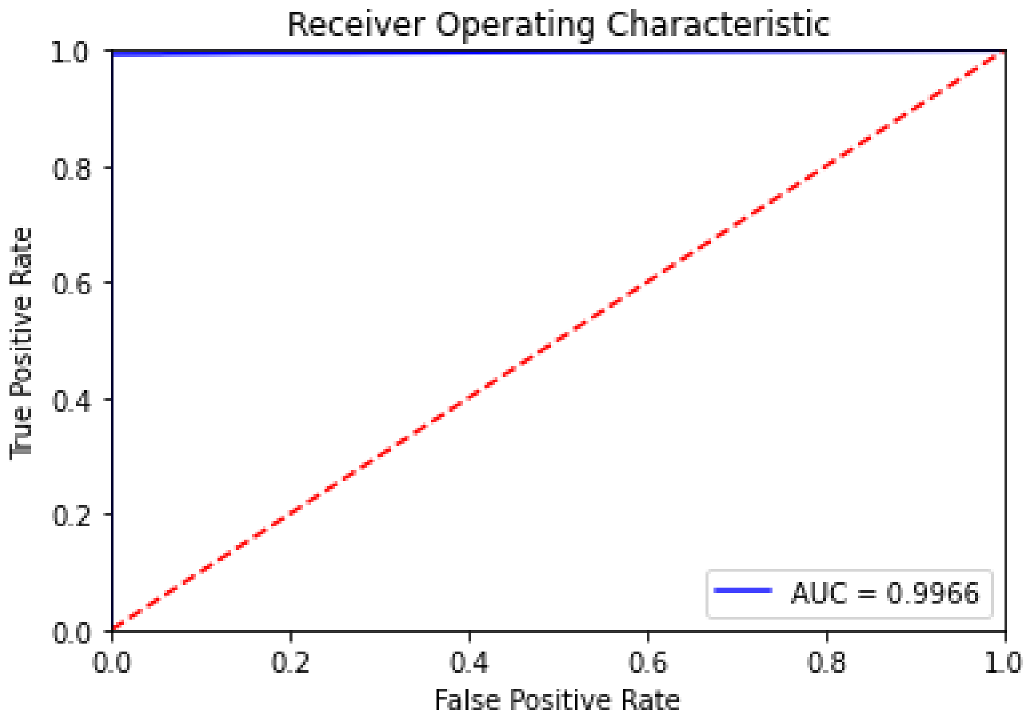
[9]:
```python
##matriz de confusión
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
cm
```

[9]:
```
array([[19246,     3],
       [   52,  7123]], dtype=int64)
```

[14]:
```python
#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()
```



Importancia de las variables del modelo

[7]:
```
from sklearn.ensemble import ExtraTreesClassifier
#Para obtener la importancia de cada variable se inicializa el␣
↪ExtraTreesClassifier
X_train=data_train_bal.iloc[:,1:23]
y_train=data_train_bal.iloc[:,0]

model_RF_imp = ExtraTreesClassifier(n_estimators = 100, n_jobs=2, criterion =␣
↪"gini", random_state = 123)

#Ajustar el modelo
model_RF_imp.fit(X_train, y_train)
```

```python
#Imprimir la importancia de cada variable
print(clas_rndforest.feature_importances_)

#Imprimir junto a los nombres de las variables
list(clas_rndforest.feature_importances_)
import pandas as pd
importancia_predictores = pd.DataFrame(
                            {'variable': X_train.columns,
                             'importancia': clas_rndforest.feature_importances_}
                            )
print("Importancia de las variables del modelo")
print("-------------------------------------------")
print("-------------------------------------------")
importancia_predictores.sort_values('importancia', ascending=False)
```

```
[0.57036956 0.21868609 0.00975929 0.00491006 0.0049352  0.00532468
 0.00458165 0.0101714  0.00706396 0.00668208 0.00476163 0.00280003
 0.00490815 0.00972466 0.02339658 0.06877393 0.02034547 0.00392972
 0.00230475 0.00434321 0.00579757 0.00643033]
Importancia de las variables del modelo
-------------------------------------------
-------------------------------------------
```

[7]:

	variable	importancia
0	Promedio_tiempo_reincidencia	0.570370
1	Prom_Tiempo_sentencia_f	0.218686
15	Sit_Actual_f_No_ingreso_CPL	0.068774
14	Sit_Actual_f_Libre	0.023397
16	Sit_Actual_f_Presente	0.020345
7	Ultimo_Delito_f_Delito_CP	0.010171
2	sexo_f	0.009759
13	Trabaja_f1	0.009725
8	Ultimo_Delito_f_Delito_CV	0.007064
9	Ultimo_Delito_f_Delito_Drogas	0.006682
21	Nivel_Instrucción_UD_f_Primaria	0.006430
20	Nivel_Instrucción_UD_f_Bachillerato	0.005798
5	grupo_edad_UD_De_30_39	0.005325
4	grupo_edad_UD_De_24_29	0.004935
3	grupo_edad_UD_De_18_23	0.004910
12	Region_UD_f_Sierra	0.004908
10	Region_UD_f_Costa	0.004762
6	grupo_edad_UD_De_40_50	0.004582
19	Estado_civil_UD_f_Soltero	0.004343
17	Estado_civil_UD_f_Casado	0.003930
11	Region_UD_f_Oriente	0.002800
18	Estado_civil_UD_f_Divorciado	0.002305

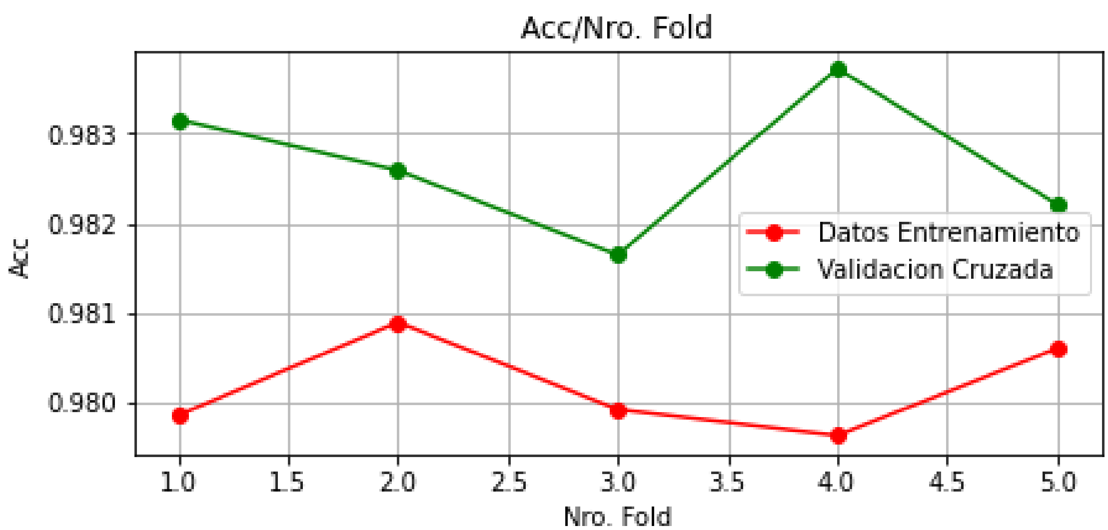
1.3 Ajustar el clasificador SVM en el Conjunto de Entrenamiento

[18]:
```
#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: [0.97985794 0.98089523 0.97992215 0.97963023
0.98060331]
Average score: 0.9802
```

[19]:
```
#Validación cruzada (gráfico y datos)
graficar_Accu_scores(class_svm,X_train,y_train,X_test,y_test,nparts=5,jobs=2)
```

[19]:
```
array([0.97985794, 0.98089523, 0.97992215, 0.97963023, 0.98060331])
```



[15]:
```
# 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)
```

[15]:
```
SVC(probability=True, random_state=123)
```

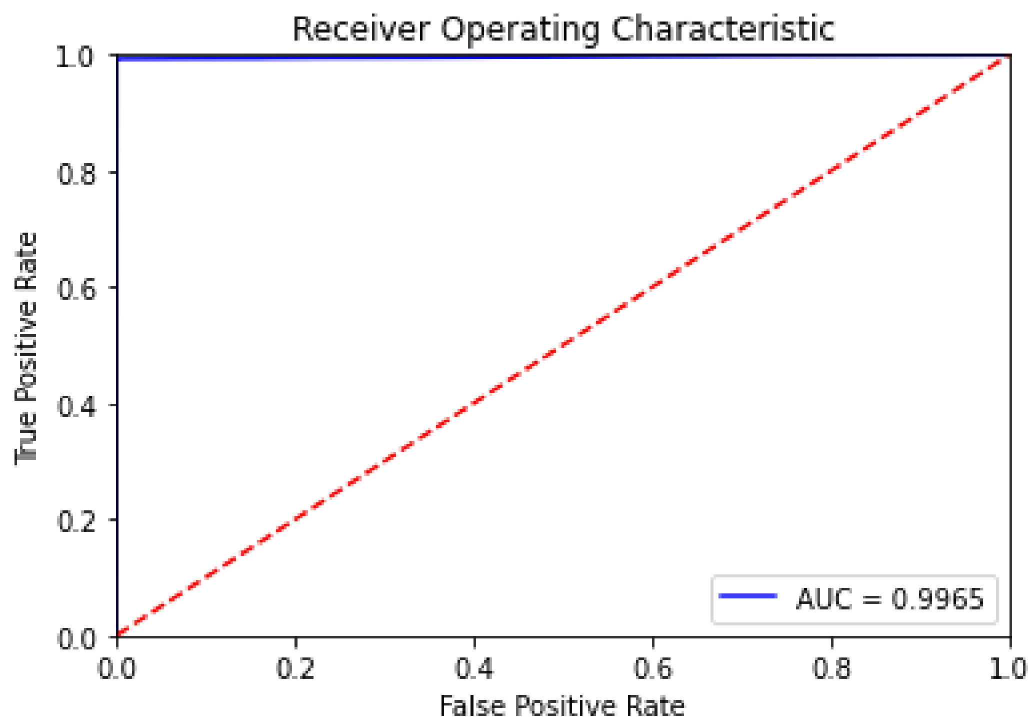
[16]:
```
# Predecir los resultados
y_pred_svm = class_svm.predict(X_test)
```

[17]:
```
# Matriz de confusión
from sklearn.metrics import confusion_matrix
cm_svm = confusion_matrix(y_test, y_pred_svm)
cm_svm # display
```

[17]:
```
array([[19249,     0],
       [  251,  6924]], dtype=int64)
```

[20]:
```
#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()
```



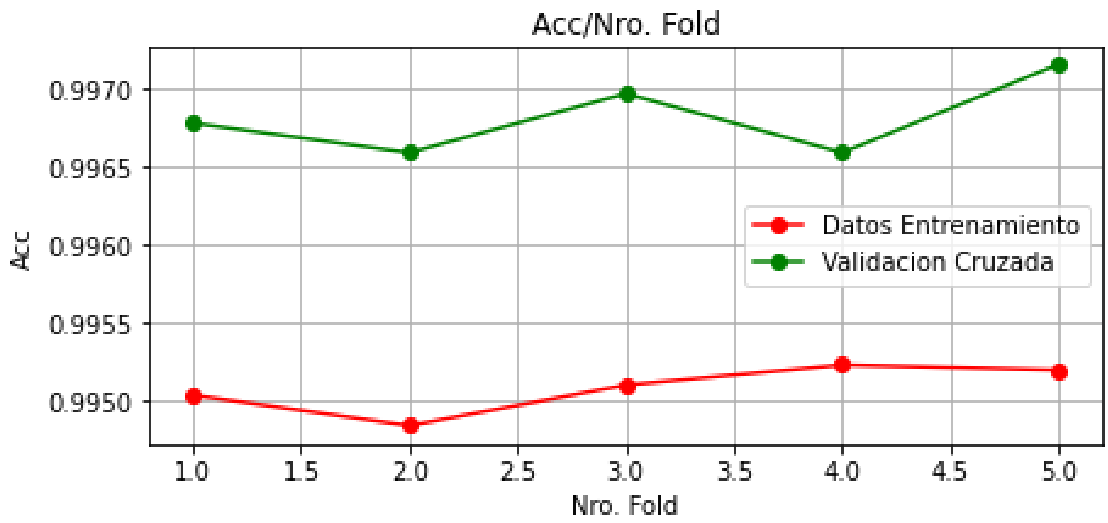
1.4 Ajustar el clasificador NAIVE BAYES en el Conjunto de Entrenamiento

[24]:
```
#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: [0.99503746 0.99484269 0.99510217 0.99523192
0.99519948]
Average score: 0.9951
```

[25]:
```
#Validación cruzada
graficar_Accu_scores(class_nb,X_train,y_train,X_test,y_test,nparts=5,jobs=2)
```

[25]:
```
array([0.99503746, 0.99484269, 0.99510217, 0.99523192, 0.99519948])
```



[21]:
```
from sklearn.naive_bayes import GaussianNB
class_nb = GaussianNB()
class_nb.fit(X_train, y_train)
```

[21]: GaussianNB()

[22]:
```
# Predecir los resultados
y_pred_nb  = class_nb.predict(X_test)
```

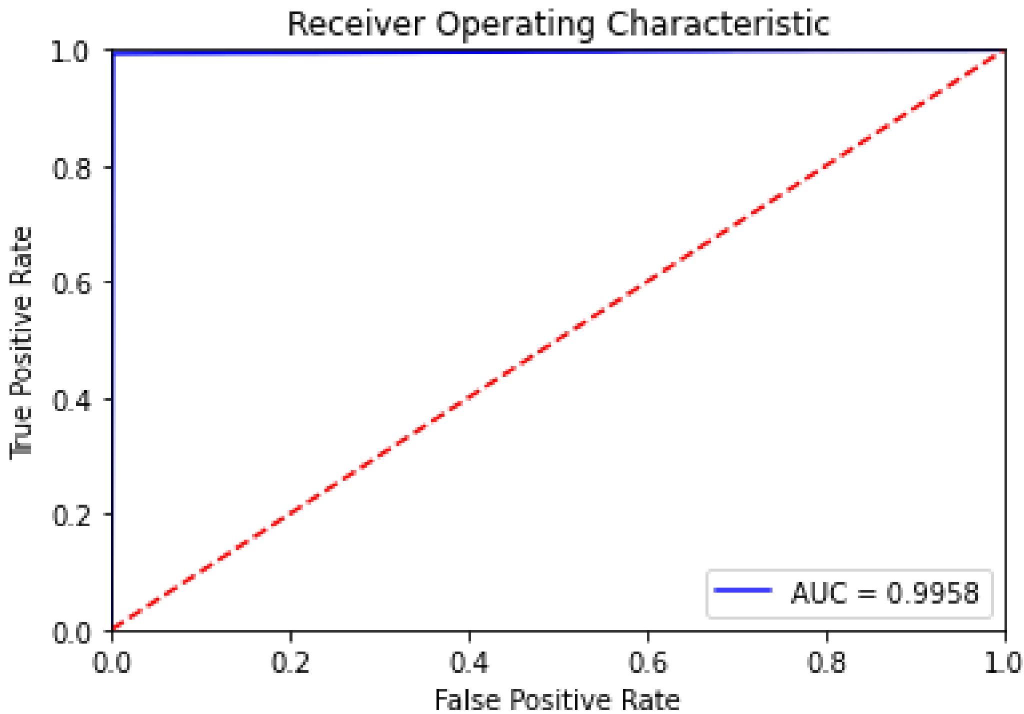
[23]:
```
# Matriz de confusión
from sklearn.metrics import confusion_matrix
cm_nb = confusion_matrix(y_test, y_pred_nb)
cm_nb # display
```

[23]:
```
array([[  130, 19119],
       [    0,  7175]], dtype=int64)
```

[26]:
```
#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()
```



1.5 Ajustar el clasificador REDES NEURONALES en el Conjunto de Entrenamiento

[33]:
```
#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_15164/2278733859.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)
```

[34]:
```
print(f'Scores for each fold are: {Accuracy}')
print(f'Average score: {"{:.4f}".format(Accuracy.mean())}')
```

```
Scores for each fold are: [0.9903993  0.9899773  0.99108011 0.9894259
0.98929614]
Average score: 0.9900
```

[5]:
```
import keras
from keras.models import Sequential
from keras.layers import Dense
```

[6]:
```
#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
```

```python
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
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0906 -
accuracy: 0.9755
Epoch 2/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0674 -
accuracy: 0.9833
Epoch 3/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0652 -
accuracy: 0.9841
Epoch 4/100
15416/15416 [==============================] - 21s 1ms/step - loss: 0.0639 -
accuracy: 0.9845
Epoch 5/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0627 -
accuracy: 0.9848
Epoch 6/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0624 -
accuracy: 0.9848
Epoch 7/100
15416/15416 [==============================] - 25s 2ms/step - loss: 0.0609 -
accuracy: 0.9854
Epoch 8/100
15416/15416 [==============================] - 23s 2ms/step - loss: 0.0598 -
accuracy: 0.9855
Epoch 9/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0594 -
accuracy: 0.9857
Epoch 10/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0584 -
accuracy: 0.9860
Epoch 11/100
15416/15416 [==============================] - 21s 1ms/step - loss: 0.0579 -
accuracy: 0.9860
Epoch 12/100
15416/15416 [==============================] - 21s 1ms/step - loss: 0.0572 -
accuracy: 0.9864
Epoch 13/100
15416/15416 [==============================] - 21s 1ms/step - loss: 0.0567 -
accuracy: 0.9863
Epoch 14/100
15416/15416 [==============================] - 21s 1ms/step - loss: 0.0570 -
accuracy: 0.9863
Epoch 15/100
```

```
15416/15416 [==============================] - 21s 1ms/step - loss: 0.0560 -
accuracy: 0.9865
Epoch 16/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0558 -
accuracy: 0.9866
Epoch 17/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0552 -
accuracy: 0.9868
Epoch 18/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0548 -
accuracy: 0.9868
Epoch 19/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0541 -
accuracy: 0.9871
Epoch 20/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0537 -
accuracy: 0.9871 0s - loss: 0.0536 - accuracy:
Epoch 21/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0540 -
accuracy: 0.9871
Epoch 22/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0530 -
accuracy: 0.9871
Epoch 23/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0513 -
accuracy: 0.9876
Epoch 24/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0518 -
accuracy: 0.9875
Epoch 25/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0510 -
accuracy: 0.9877
Epoch 26/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0509 -
accuracy: 0.9879
Epoch 27/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0502 -
accuracy: 0.9880
Epoch 28/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0509 -
accuracy: 0.9878
Epoch 29/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0507 -
accuracy: 0.9879
Epoch 30/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0500 -
accuracy: 0.9881
Epoch 31/100
```

```
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0494 -
accuracy: 0.9882
Epoch 32/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0486 -
accuracy: 0.9885
Epoch 33/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0486 -
accuracy: 0.9885
Epoch 34/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0493 -
accuracy: 0.9883
Epoch 35/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0480 -
accuracy: 0.9886
Epoch 36/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0480 -
accuracy: 0.9886
Epoch 37/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0463 -
accuracy: 0.9890
Epoch 38/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0472 -
accuracy: 0.9888
Epoch 39/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0468 -
accuracy: 0.9890
Epoch 40/100
15416/15416 [==============================] - 32s 2ms/step - loss: 0.0469 -
accuracy: 0.9889
Epoch 41/100
15416/15416 [==============================] - 27s 2ms/step - loss: 0.0463 -
accuracy: 0.9892
Epoch 42/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0454 -
accuracy: 0.9893
Epoch 43/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0454 -
accuracy: 0.9893
Epoch 44/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0458 -
accuracy: 0.9892
Epoch 45/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0460 -
accuracy: 0.9891
Epoch 46/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0455 -
accuracy: 0.9894
Epoch 47/100
```

```
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0455 -
accuracy: 0.9893
Epoch 48/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0447 -
accuracy: 0.9894
Epoch 49/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0448 -
accuracy: 0.9895
Epoch 50/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0445 -
accuracy: 0.9895
Epoch 51/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0441 -
accuracy: 0.9897
Epoch 52/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0442 -
accuracy: 0.9896
Epoch 53/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0440 -
accuracy: 0.9897
Epoch 54/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0434 -
accuracy: 0.9899
Epoch 55/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0441 -
accuracy: 0.9897
Epoch 56/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0431 -
accuracy: 0.9898
Epoch 57/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0438 -
accuracy: 0.9897
Epoch 58/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0441 -
accuracy: 0.9898
Epoch 59/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0435 -
accuracy: 0.9900
Epoch 60/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0431 -
accuracy: 0.9899
Epoch 61/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0438 -
accuracy: 0.9899
Epoch 62/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0432 -
accuracy: 0.9899
Epoch 63/100
```

```
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0430 -
accuracy: 0.9901
Epoch 64/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0426 -
accuracy: 0.9903
Epoch 65/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0420 -
accuracy: 0.9903
Epoch 66/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0429 -
accuracy: 0.9901
Epoch 67/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0426 -
accuracy: 0.9900
Epoch 68/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0424 -
accuracy: 0.9903
Epoch 69/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0420 -
accuracy: 0.9903
Epoch 70/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0432 -
accuracy: 0.9899
Epoch 71/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0413 -
accuracy: 0.9905
Epoch 72/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0416 -
accuracy: 0.9902
Epoch 73/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0418 -
accuracy: 0.9904
Epoch 74/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0417 -
accuracy: 0.9903
Epoch 75/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0413 -
accuracy: 0.9903
Epoch 76/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0406 -
accuracy: 0.9906
Epoch 77/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0413 -
accuracy: 0.9904
Epoch 78/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0411 -
accuracy: 0.9905
Epoch 79/100
```

```
15416/15416 [==============================] - 21s 1ms/step - loss: 0.0409 -
accuracy: 0.9906
Epoch 80/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0410 -
accuracy: 0.9905
Epoch 81/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0404 -
accuracy: 0.9906
Epoch 82/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0402 -
accuracy: 0.9907
Epoch 83/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0402 -
accuracy: 0.9906
Epoch 84/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0403 -
accuracy: 0.9908
Epoch 85/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0407 -
accuracy: 0.9907
Epoch 86/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0406 -
accuracy: 0.9907
Epoch 87/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0402 -
accuracy: 0.9907
Epoch 88/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0399 -
accuracy: 0.9907
Epoch 89/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0399 -
accuracy: 0.9907
Epoch 90/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0401 -
accuracy: 0.9907
Epoch 91/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0392 -
accuracy: 0.9908
Epoch 92/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0395 -
accuracy: 0.9908
Epoch 93/100
15416/15416 [==============================] - 17s 1ms/step - loss: 0.0392 -
accuracy: 0.9908
Epoch 94/100
15416/15416 [==============================] - 20s 1ms/step - loss: 0.0394 -
accuracy: 0.9909
Epoch 95/100
```

```
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0390 -
accuracy: 0.9909 0s -
Epoch 96/100
15416/15416 [==============================] - 18s 1ms/step - loss: 0.0394 -
accuracy: 0.9908
Epoch 97/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0393 -
accuracy: 0.9910
Epoch 98/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0392 -
accuracy: 0.9908
Epoch 99/100
15416/15416 [==============================] - 19s 1ms/step - loss: 0.0394 -
accuracy: 0.9908
Epoch 100/100
15416/15416 [==============================] - 21s 1ms/step - loss: 0.0389 -
accuracy: 0.9910 0s - loss: 0.0387 -
```

[6]:
```
<keras.callbacks.History at 0x275b601c190>
```

[7]:
```python
test_loss, test_acc = class_RN.evaluate(X_test,  y_test, verbose=2)
print('\nTest Accuracy:', test_acc)
```

```
826/826 - 1s - loss: 0.0259 - accuracy: 0.9956 - 832ms/epoch - 1ms/step

Test Accuracy: 0.9955722093582153
```

[8]:
```python
# 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)
```

[9]:
```python
#Elaborar una matriz de confusión
from sklearn.metrics import confusion_matrix
cm_rn = confusion_matrix(y_test, y_pred_rn)
cm_rn
```

[9]:
```
array([[19243,     6],
       [  111,  7064]], dtype=int64)
```

[10]:
```python
#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()
```