COGNITO

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MACHINE LEARNING
UNSAM 2021

HEART FAILURE PREDICTION

D A T A S E T
299 PACIENTES 12 FEATURES 1 TARGET

BINARIAS

anaemia: Disminución de glóbulos rojos o hemoglobina
sex: Mujer u hombre
smoking: Si el paciente fuma
diabetes: Si el paciente tiene diabetes
high_blood_pressure: Si el paciente tiene hipertensión

CONTINUAS

age: Edad del paciente (años)
creatinine_phosphokinase: Nivel de enzimas CPK en sangre (mcg/L)
ejection_fraction: Porcentaje de sangre eyectada del corazón por contracción (%)
platelets: Plaquetas en sangre (kiloplatelets/mL)
serum_creatinine: Nivel de creatinina sérica en sangre (mg/dL)
serum_sodium: Nivel de sodio sérica en sangre (mEq/L)
time: Periodo de seguimiento (días)

TARGET

DEATH_EVENT: Si el paciente falleció durante el periodo de seguimiento

F u e n t e : https://www.kaggle.com/andrewmvd/heart-failure-clinical-data

ALGUNAS OBSERVACIONES

creatinine_phosphokinase.mean() = 581.8 mcg/L (valor normal <120)
Valores altos en pacientes con AC o Pericarditis posterior a un AC

ejection_fraction.mean() = 38% (valor mínimo crítico = 41%)
La disminución puede deberse a un AC o Alta Presión

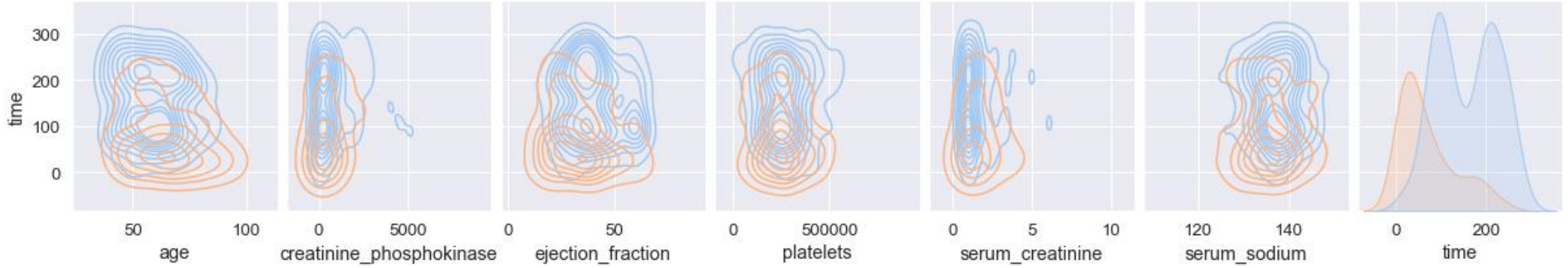
serum_creatinine.mean() = 1.4 mg/dL (valor normal: mujeres < 1.1, hombres < 1.3)
Valores altos indican problemas renales, muy relacionado con la presión y el corazón

serum_sodium.mean() = 136.7 mEq/L (valores normales 135-140)

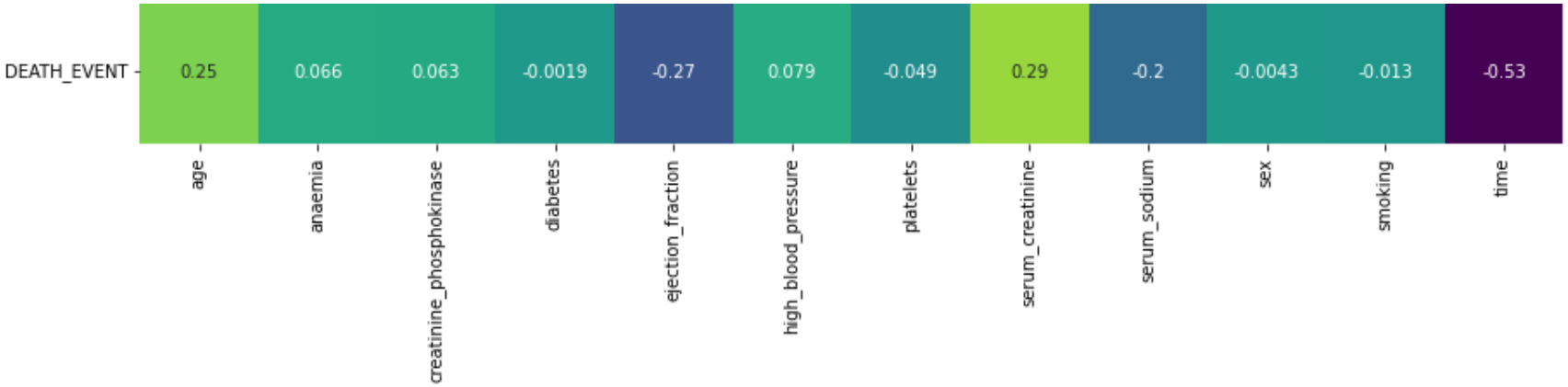
platelets.mean() = 98k/mL (valor mínimo normal = 150)

En general, los valores están por fuera de lo normal, lo que indica que los pacientes sufren definitivamente complicaciones relacionadas.

También se concluyó que el feature "time" era muy determinante y, en la práctica, indeterminable.
Por lo que se decidió dropear este feature.



SELECCIÓN DE FEATURES



De la matriz de correlación reconocemos que los features binaries (patologías de base) son poco determinantes del target.
Para confirmar la hipótesis y descartarlos utilizamos RFECV:

RFECV o “Recursive Feature Elimination with Cross-Validation” es una herramienta de sklearn.feature_selection que verifica las feature_importance de un Random Forest grande en validación cruzada.

```
('age', True) ('anaemia', False)
('creatinine_phosphokinase', True)
('diabetes', False) ('ejection_fraction',
True) ('high_blood_pressure', False)
('platelets', True) ('serum_creatinine',
True) ('serum_sodium', True) ('sex', False)
('smoking', False) ('time', True)
```

PREPROCESADO FINAL

Con los 6 features decididos (variables continuas sin time) y los datos de entrenamiento recortados:

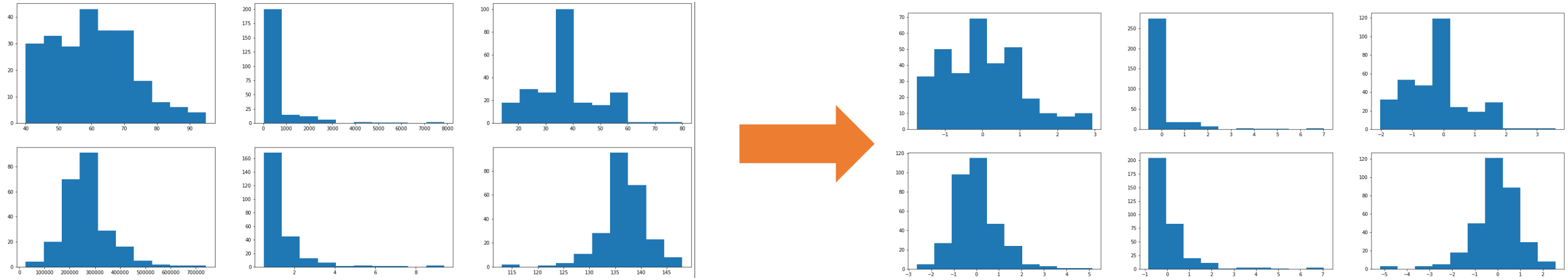
Primero estandarizamos los datos usando **StandardScaler()** del módulo de *sklearn.preprocessing* ya que para la mayoría de los algoritmos de clasificación es casi una condición necesaria.

Luego decidimos realizar un **oversampling** de los datos por 2 motivos:

- Desbalance de clases target (163 “0s” vs 76 “1s”).
- Dataset chico sumado a los splits de testeo.

Entonces aplicamos la función **SMOTE**.
SMOTE es un algoritmo de oversampleo de la libreria de imblearn (imbalanced learn) desarrollada por el MIT

Como resultado, obtenemos un dataset balanceado 50-50 de 326 samples.



BASELINE

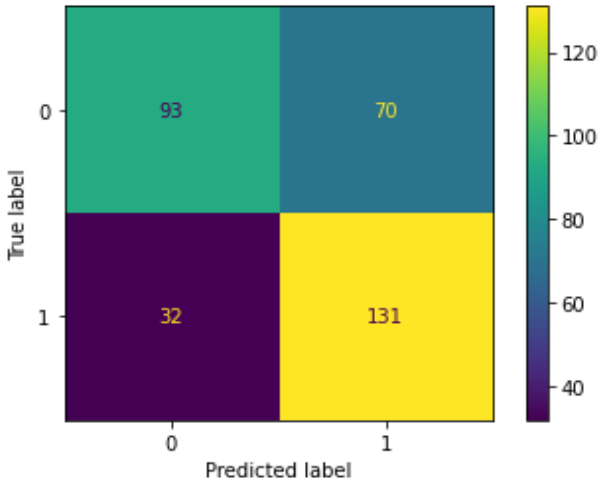
Definimos la métrica a utilizar: **RECALL**

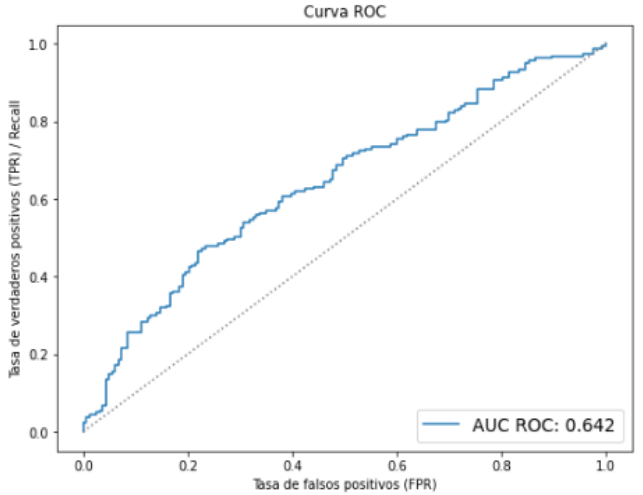
Queremos reducir los FN, es decir, pacientes que diríamos que NO tienen riesgo pero SI lo tienen en realidad.

Perceptron

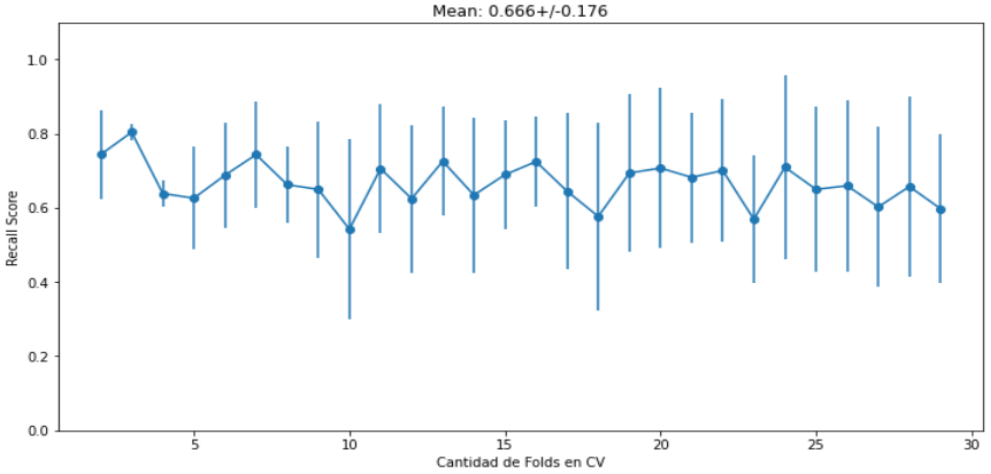
Cross Validation Score: 0.542 +/- 0.242

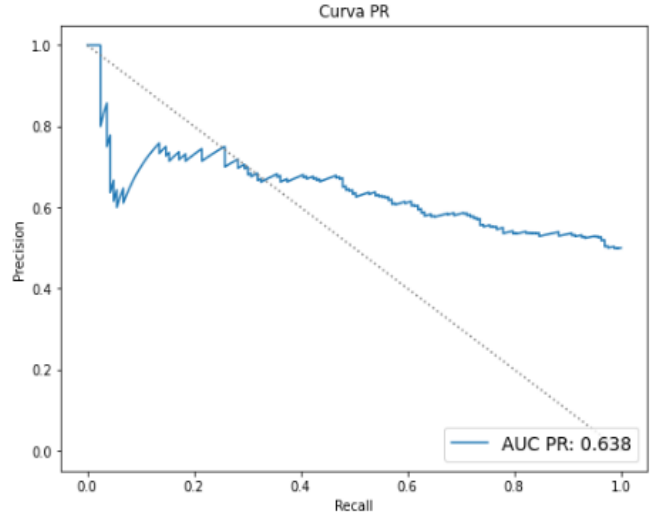
	precision	recall	f1-score	support
0	0.74	0.57	0.65	163
1	0.65	0.80	0.72	163
accuracy			0.69	326
macro avg	0.70	0.69	0.68	326
weighted avg	0.70	0.69	0.68	326





Observamos que el score tiene muy alta desviación





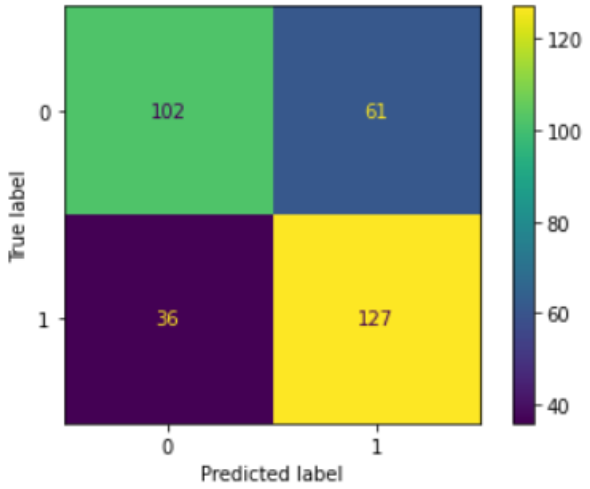
Perceptron Optimizado

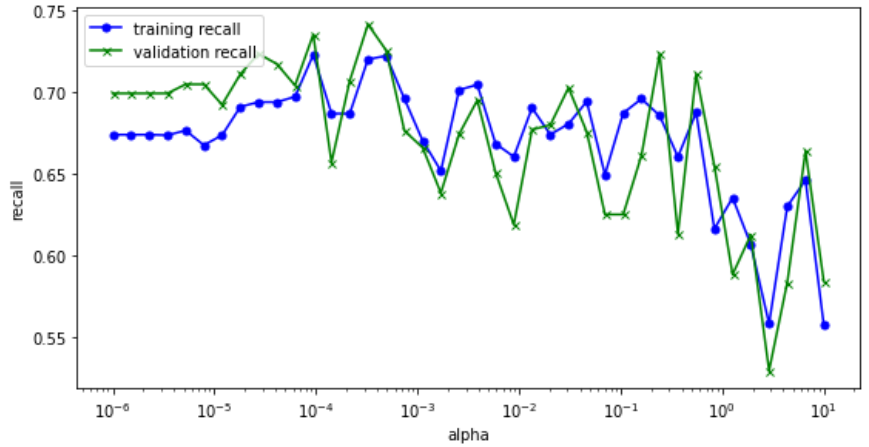
max_iter = 40000
Penalty = "l2"
Alpha = 1e-3
Eta0 = 0.04

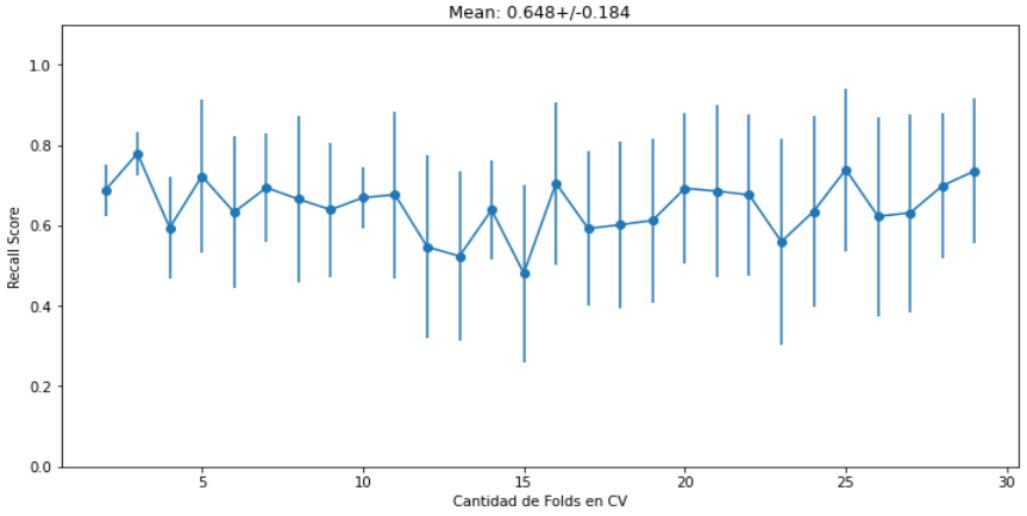
Para optimizar utilizamos “GridSearchCV” para un trazo grueso y “validation_curve” para ajustes finos, ambos del paquete de sklearn.model_selection

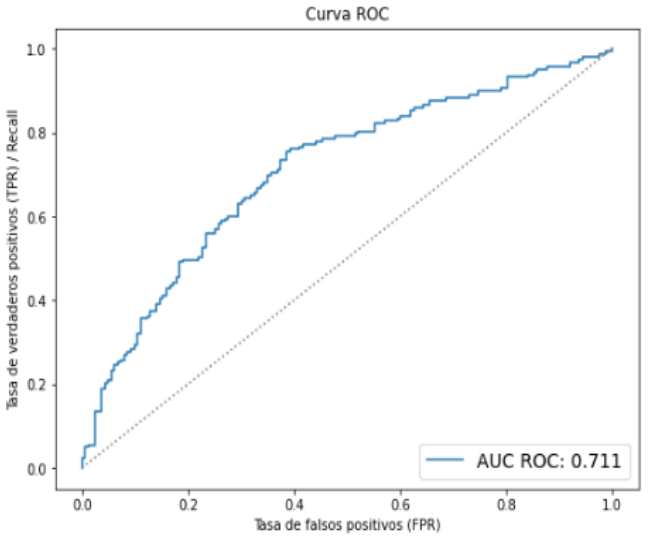
Cross Validation Score: 0.669 +/- 0.076

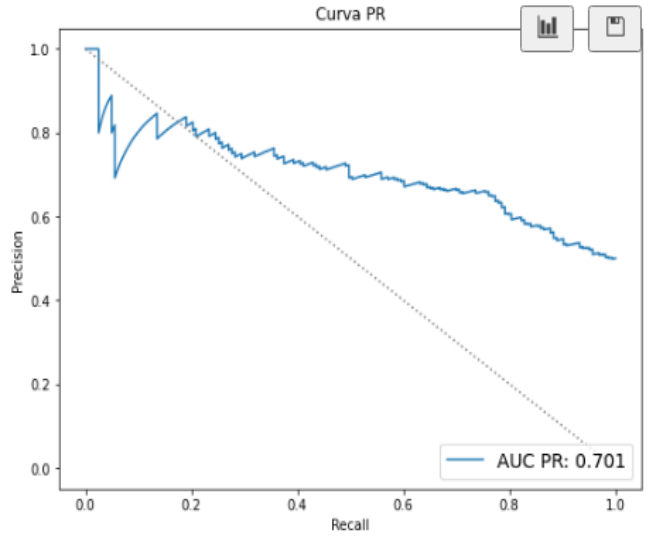
	precision	recall	f1-score	support
0	0.74	0.63	0.68	163
1	0.68	0.78	0.72	163
accuracy			0.70	326
macro avg	0.71	0.70	0.70	326
weighted avg	0.71	0.70	0.70	326







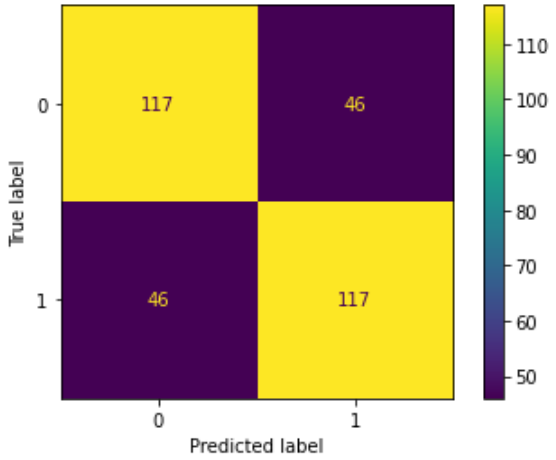


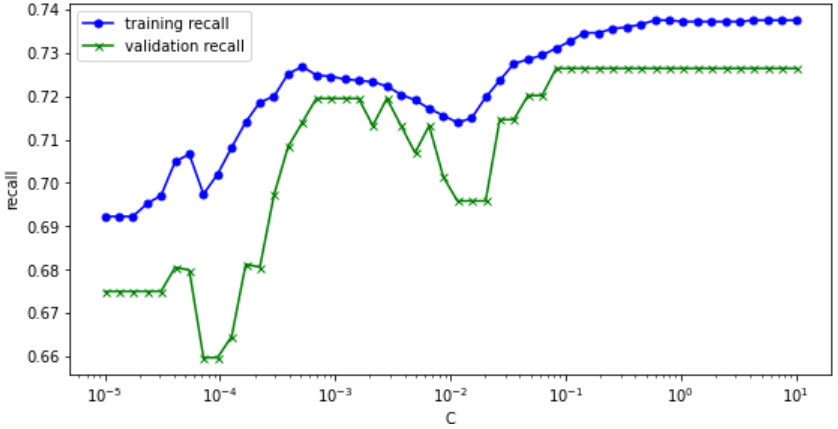


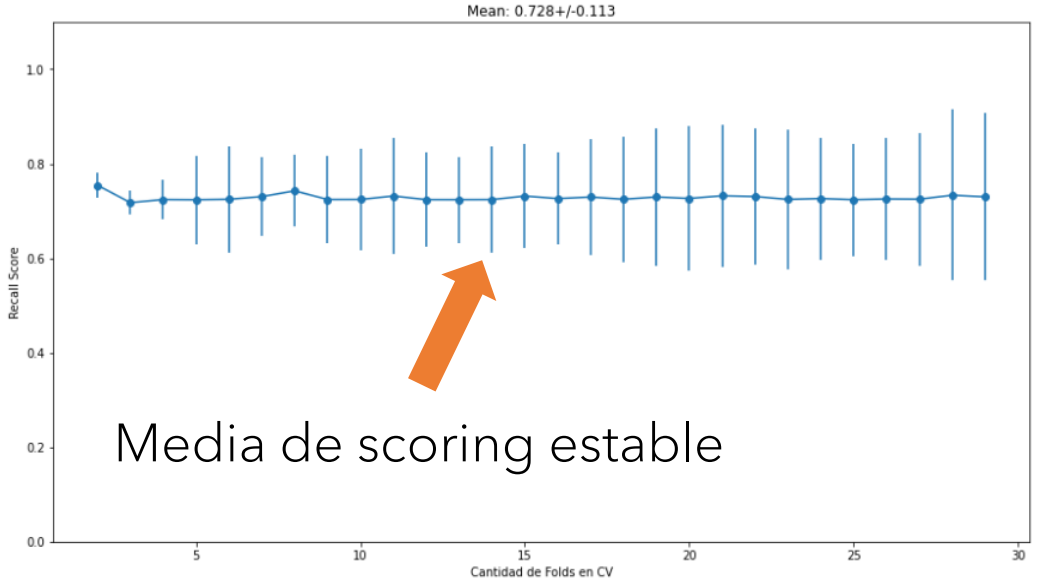
Logistic Regression

Cross Validation Score: 0.724 +/- 0.108

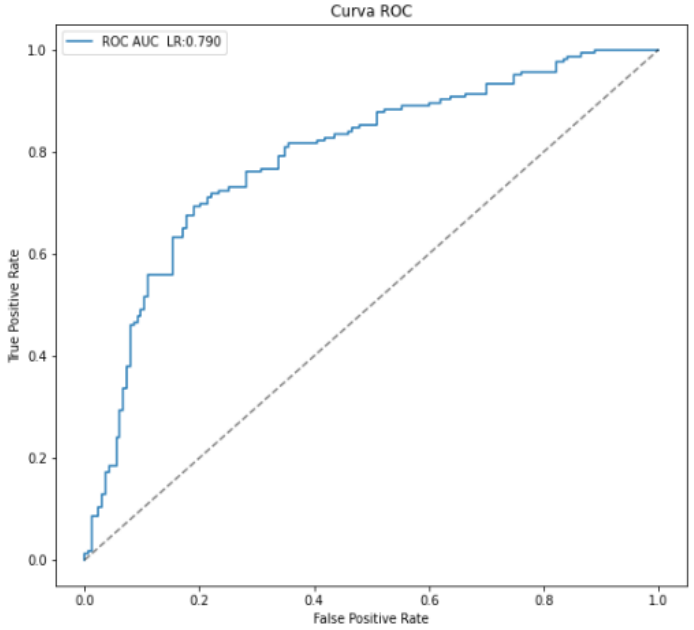
	precision	recall	f1-score	support
0	0.72	0.72	0.72	163
1	0.72	0.72	0.72	163
accuracy			0.72	326
macro avg	0.72	0.72	0.72	326
weighted avg	0.72	0.72	0.72	326

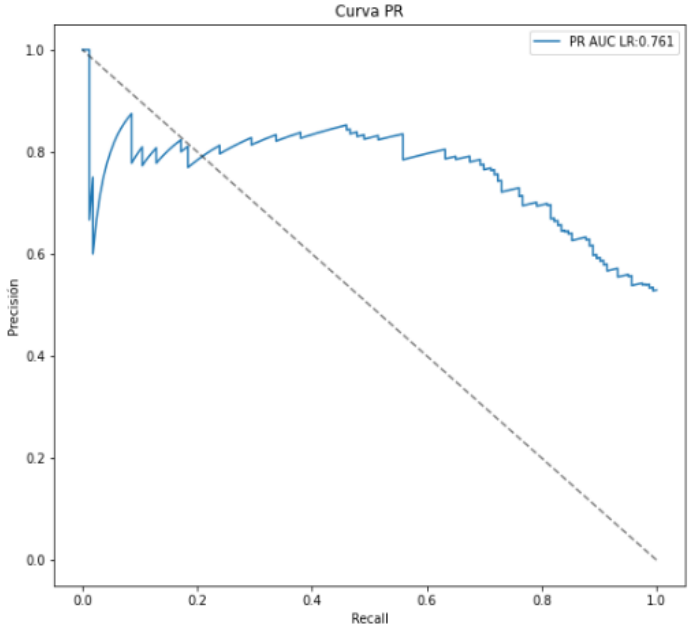






Media de scoring estable



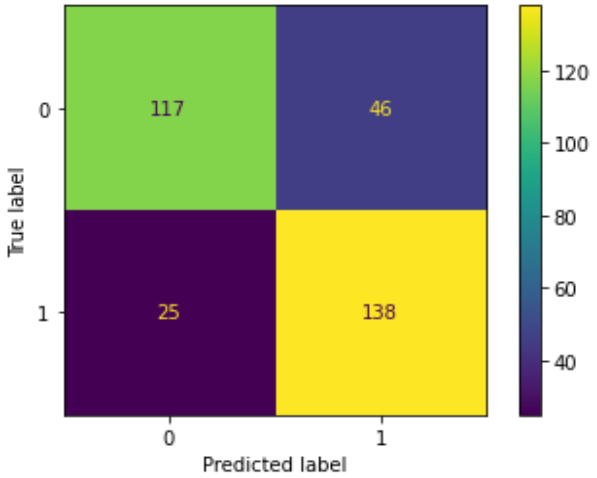


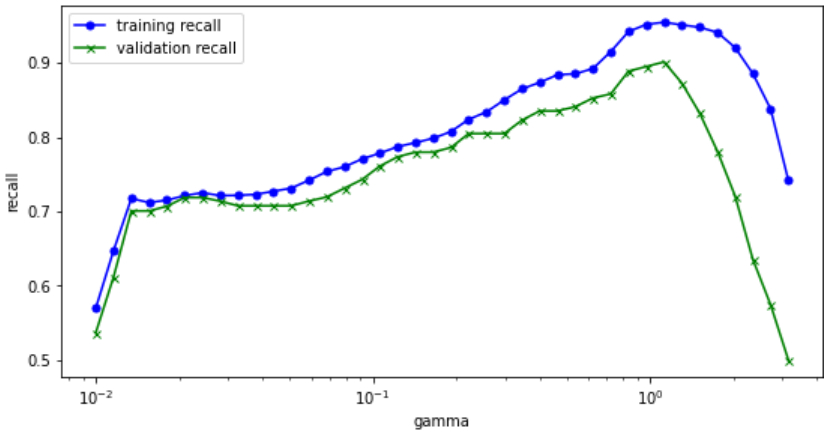
SVC

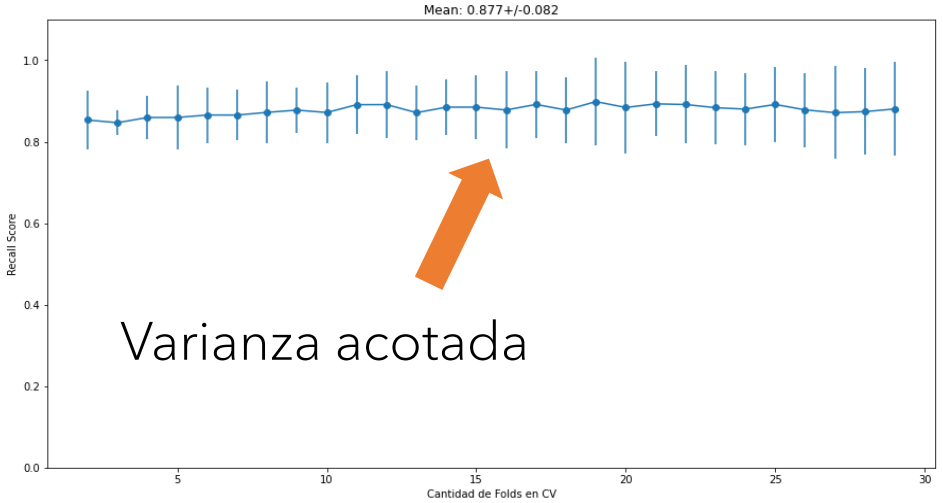
Kernel = rbf
Gamma = 1.17
C = 0.15

Cross Validation Score: 0.872 +/- 0.075

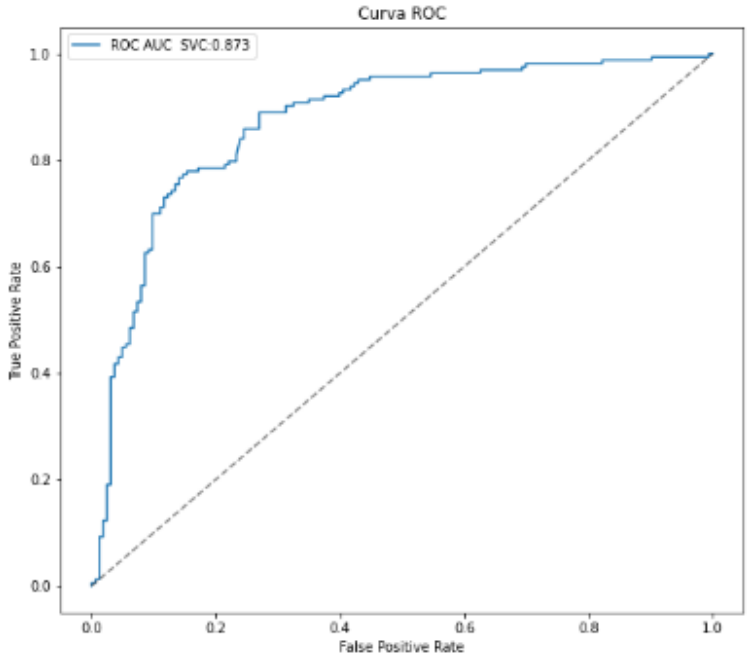
	precision	recall	f1-score	support
0	0.82	0.72	0.77	163
1	0.75	0.85	0.80	163
accuracy			0.78	326
macro avg	0.79	0.78	0.78	326
weighted avg	0.79	0.78	0.78	326

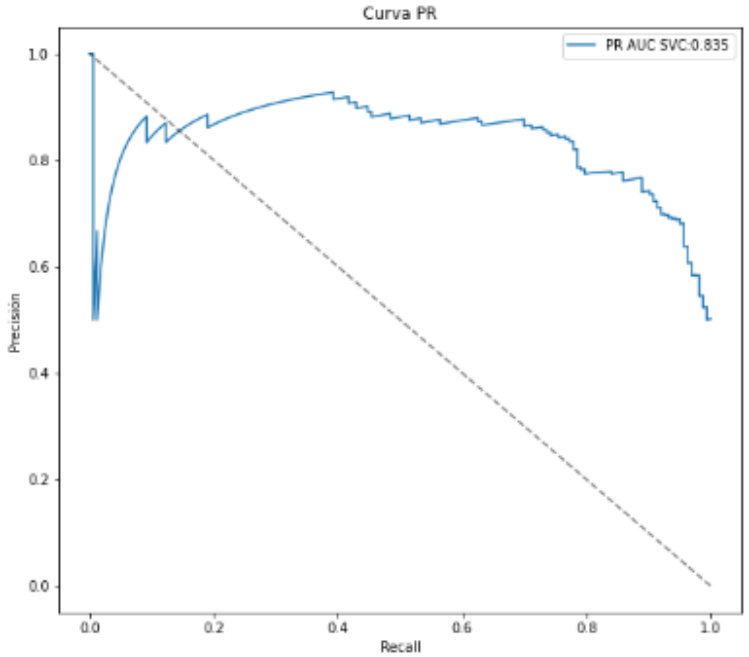






Varianza acotada



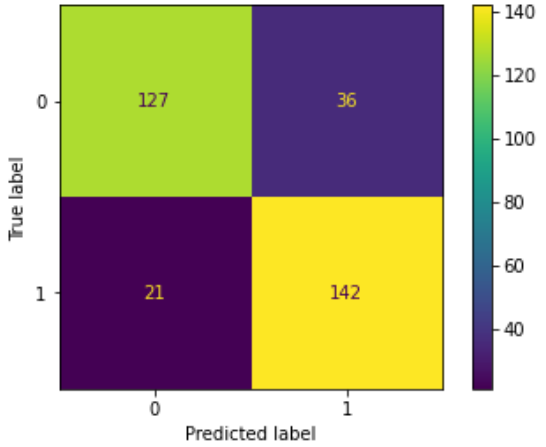


Random Forest

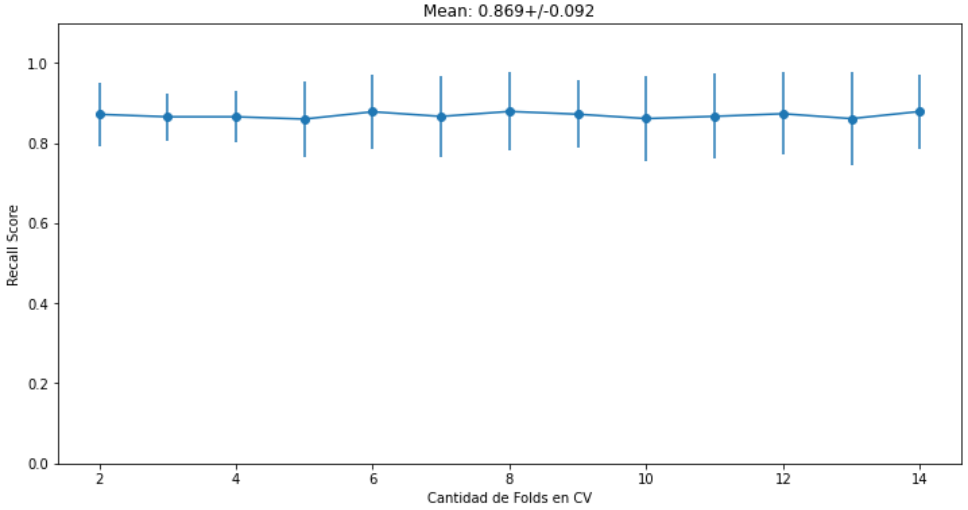
n_estimators = 400
min_impurity_decrease = 2e-4
max_depth = 8

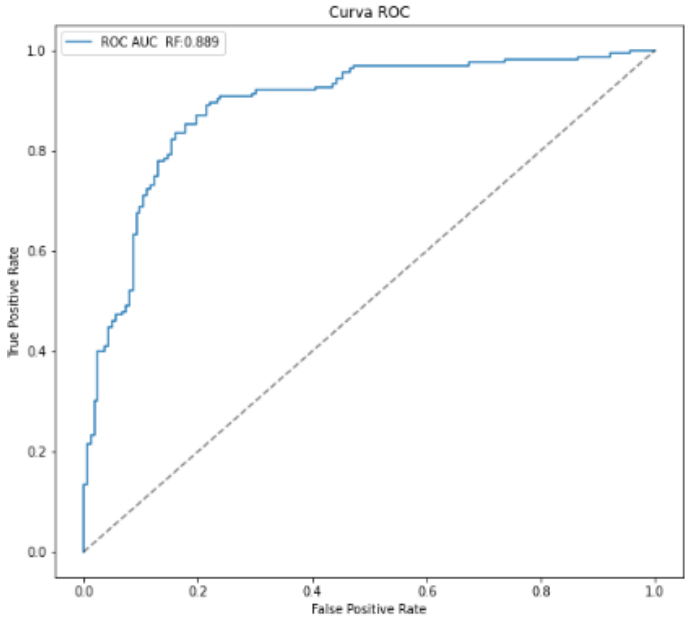
Cross Validation Score: 0.867 +/- 0.109

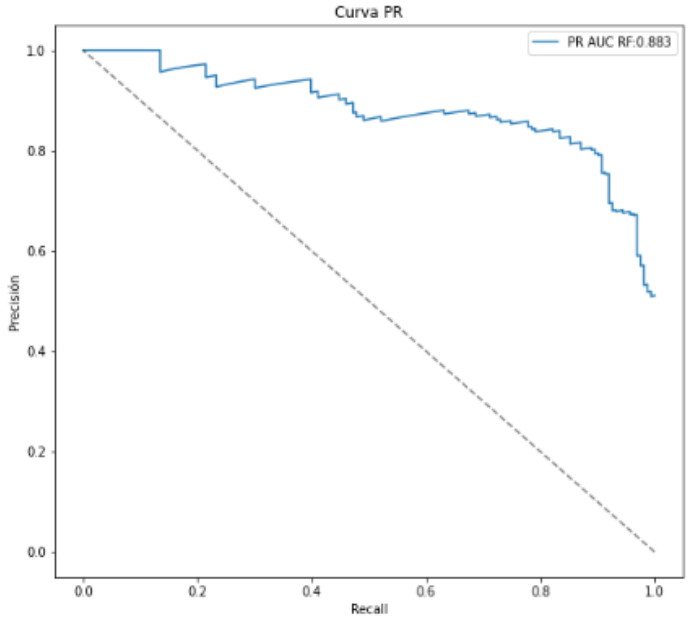
	precision	recall	f1-score	support
0	0.86	0.78	0.82	163
1	0.80	0.87	0.83	163
accuracy			0.83	326
macro avg	0.83	0.83	0.82	326
weighted avg	0.83	0.83	0.82	326



La hiperparametrización en Decision Trees y Random Forest no dió resultados notorios.





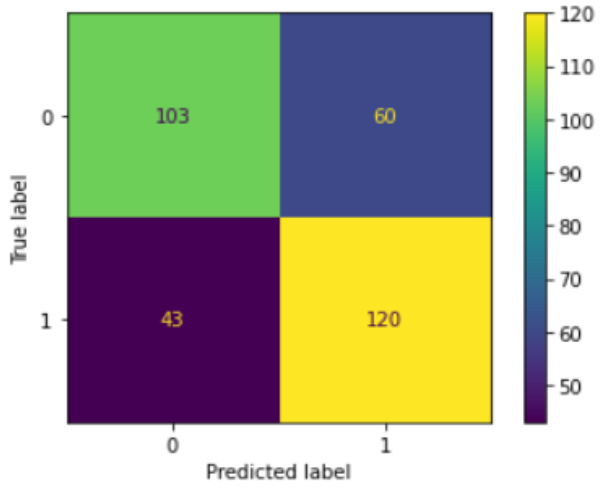


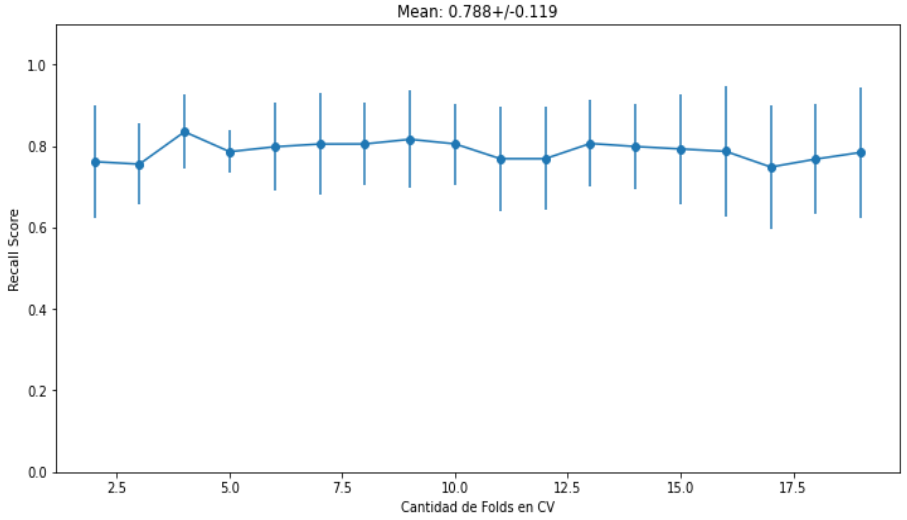
ADA Boosting

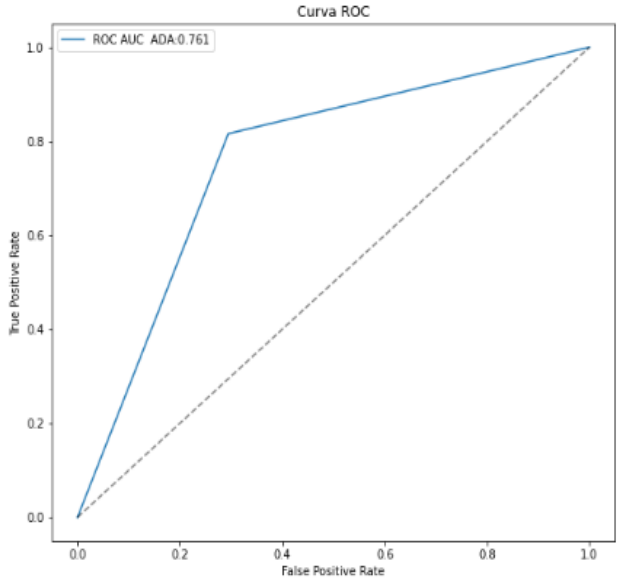
base_estimator = DecisionTreeClassifier()
learning_rate = 0.2

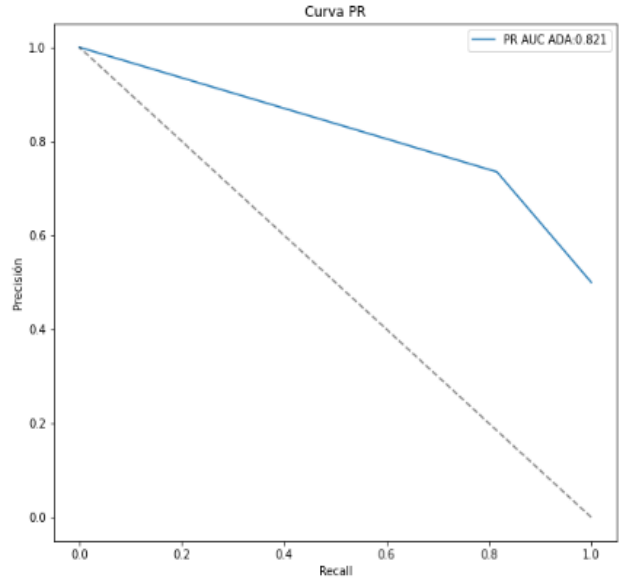
Cross Validation Score: 0.811 +/- 0.077

	precision	recall	f1-score	support
0	0.71	0.63	0.67	163
1	0.67	0.74	0.70	163
accuracy			0.68	326
macro avg	0.69	0.68	0.68	326
weighted avg	0.69	0.68	0.68	326





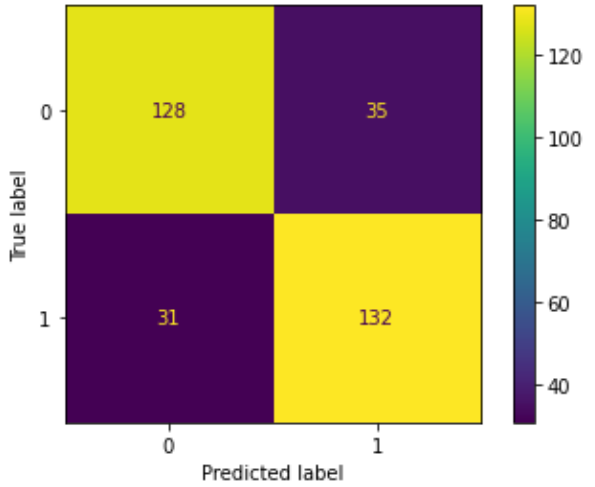




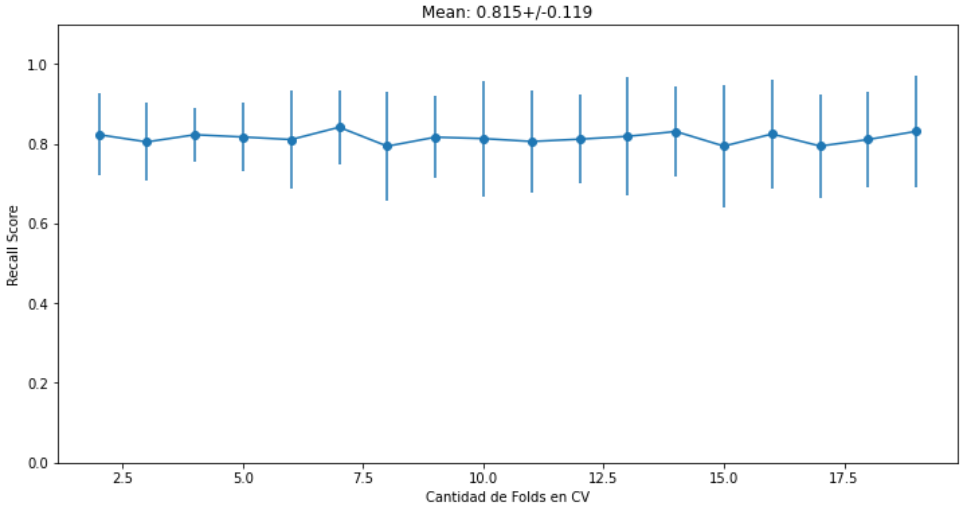
Extreme Gradient Boosting

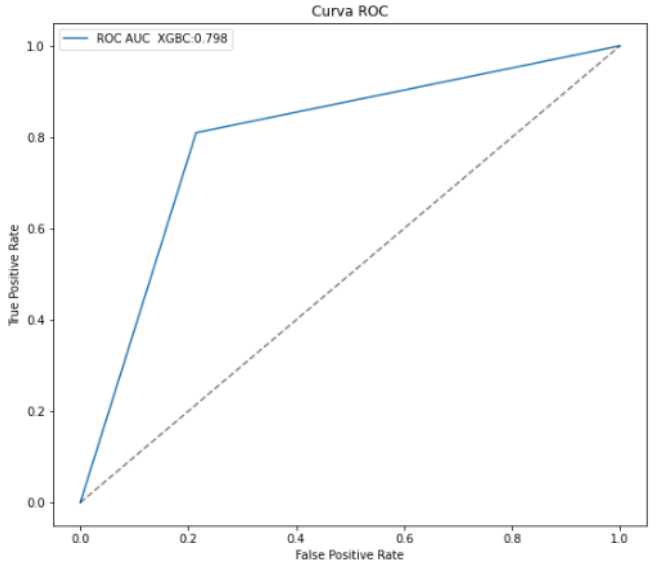
use_label_encoder = False
Objective = 'binary:hinge'
learning_rate = 0.05
n_estimators = 500

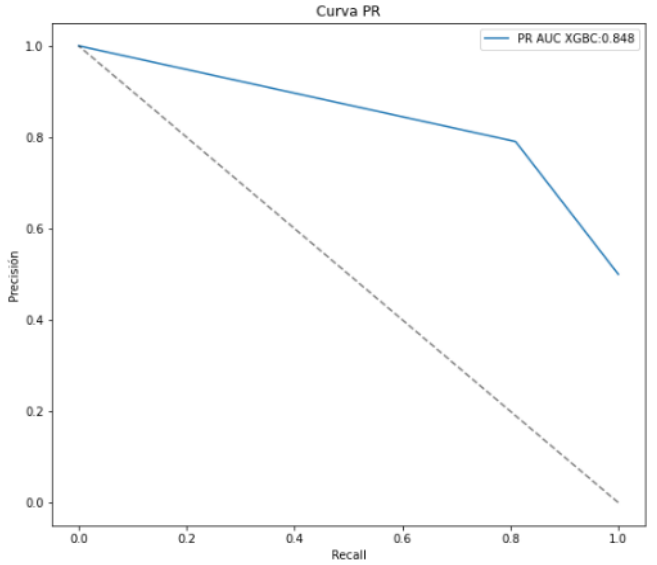
	precision	recall	f1-score	support
0	0.81	0.79	0.80	163
1	0.79	0.81	0.80	163
accuracy			0.80	326
macro avg	0.80	0.80	0.80	326
weighted avg	0.80	0.80	0.80	326



El algoritmo dio buenos resultados considerando que necesita datos para validación y los splits en nuestro dataset son muy costosos.



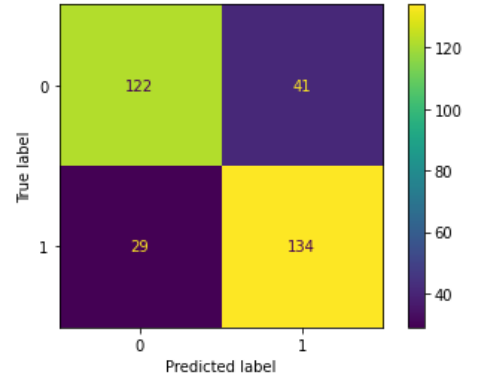




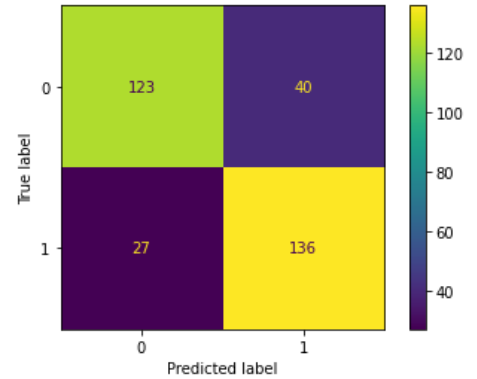
Voting Soft y Hard

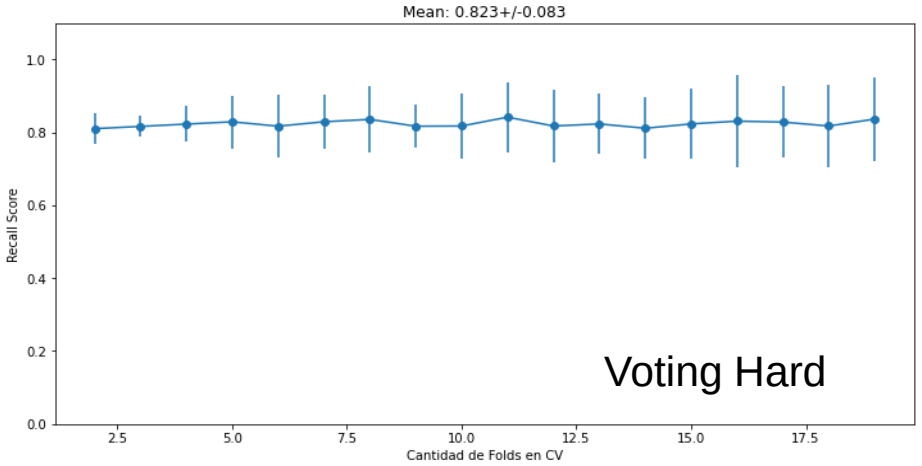
Usamos los 3 algoritmos parametrizados que consideramos mejores: RF, LR y SVC

```
Cross Validation Score: 0.829 +/- 0.083
              precision    recall  f1-score   support

           0       0.81      0.75      0.78       163
           1       0.77      0.82      0.79       163

    accuracy                           0.79       326
   macro avg       0.79      0.79      0.78       326
weighted avg       0.79      0.79      0.78       326
```

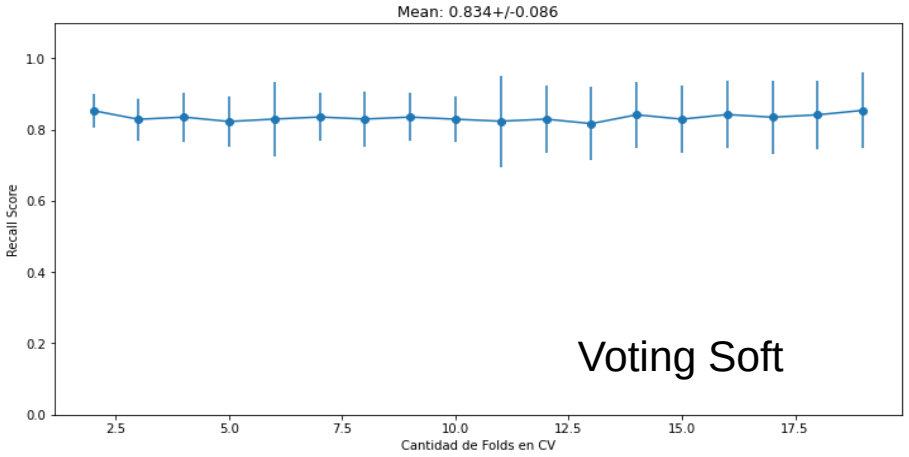



```
Cross Validation Score: 0.830 +/- 0.082
              precision    recall  f1-score   support

           0       0.82      0.75      0.79       163
           1       0.77      0.83      0.80       163

    accuracy                           0.79       326
   macro avg       0.80      0.79      0.79       326
weighted avg       0.80      0.79      0.79       326
```

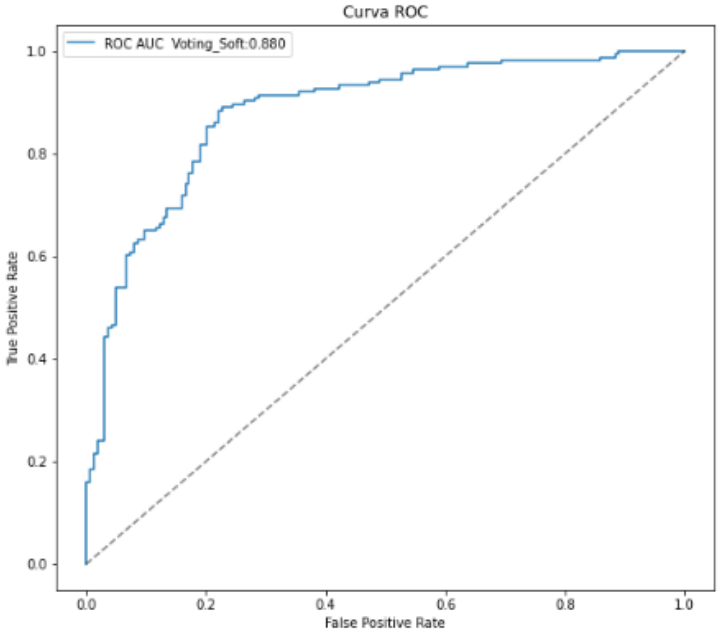


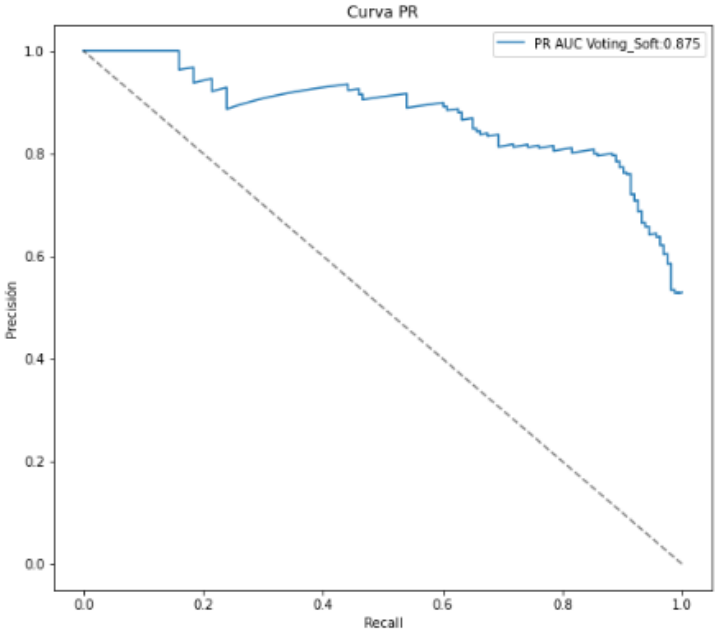


Voting Hard



Voting Soft

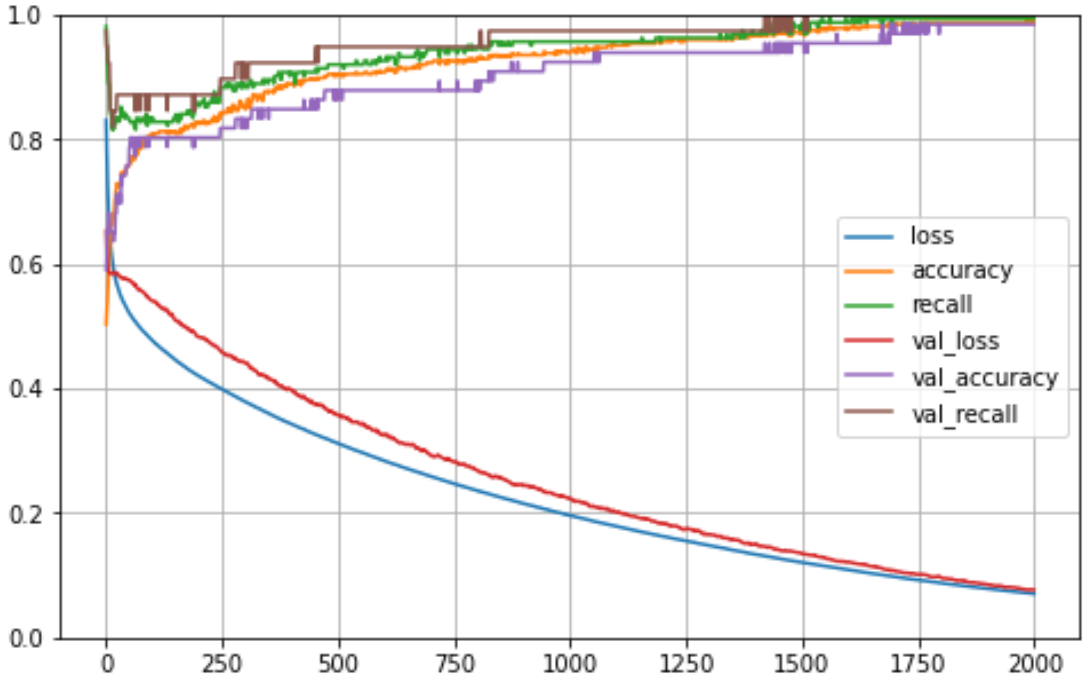




Neuronal Network

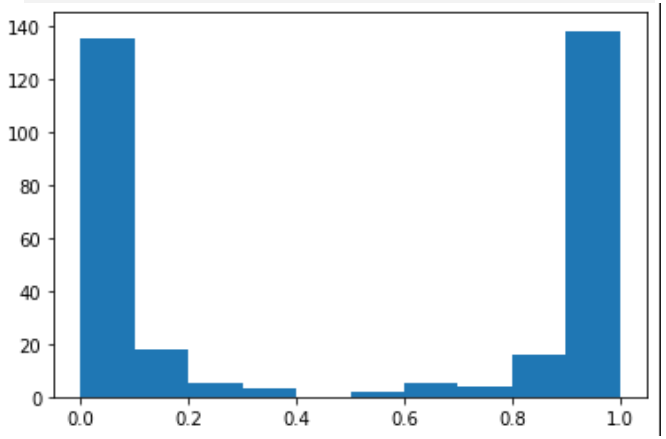
Loss: Binary Cross-Entropy
Optimizer: Adam (lr = 5e-5)
Metrics: Recall,Accuracy
Epochs: 2000
Batch = 32
Earling Stopping (100)

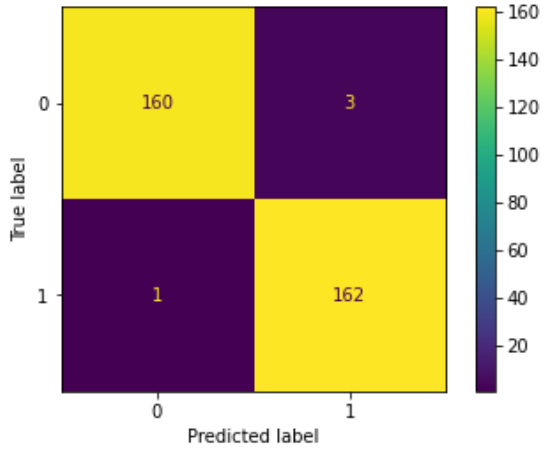
```
input = keras.layers.Input(shape=[6,])
flatten = keras.layers.Flatten()(input)
hidden1 = keras.layers.Dense(100, activation="relu",kernel_initializer='he_uniform')(flatten)
dropout = keras.layers.Dropout(rate=0.2)(hidden1)
hidden2 = keras.layers.Dense(100, activation="relu",kernel_initializer='he_uniform')(hidden1)
output = keras.layers.Dense(1, activation="sigmoid")(hidden2)
model = keras.models.Model(inputs=[input], outputs=[output])
```




```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 6)]               0
_________________________________________________________________
flatten (Flatten)            (None, 6)                 0
_________________________________________________________________
dense (Dense)                (None, 100)               700
_________________________________________________________________
dense_1 (Dense)              (None, 100)               10100
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 101
=================================================================
Total params: 10,901
Trainable params: 10,901
Non-trainable params: 0
```

```
plt.hist(model.predict(feat_train))
```






```
Epoch 463/600
9/9 [==============================] - 0s 2ms/step - loss: 0.0067 - recall: 1.0000 - val_loss: 0.1678 - val_recall: 0.9394
```

En resumen…

- Las hiperparametrización logró mejorar el score de entrenamiento en todos los casos.
- La incorporación de “Time” mejora el recall notoriamente.
- Hay una caída sustancial en los scorings de testing. Era esperable tras observar la alta varianza en entrenamiento.
- Se observó mejores resultados en modelos con más “bias”.
- SMOTE fue una herramienta indispensable para nuestro análisis y los scorings.

algoritmo	s/time	c/time	test
Per (BL)	0.542	0.721	0.538
Per_op	0.773	0.731	0.400
LR_op	0.731	0.811	0.667
SVC_op	0.895	0.916	0.586
RF_op	0.872	0.917	0.667
ADA_op	0.811	0.837	0.526
XGBC_op	0.813	0.905	0.579
VotHard	0.865	0.916	0.652
VotSoft	0.836	0.910	0.619
ANN	0.954	0.984	0.736