

```
# gerardo Herrera... random forest (500 arboles) con 28k instancias de normal y recovering y 2

import numpy as np
import pandas as pd
import os

import matplotlib.pyplot as plt
%matplotlib inline
from tqdm import tqdm_notebook
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error
pd.options.display.precision = 15

import time
# Libraries
import numpy as np
import pandas as pd
pd.set_option('max_columns', None)
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

!pip install lightgbm
!pip install catboost

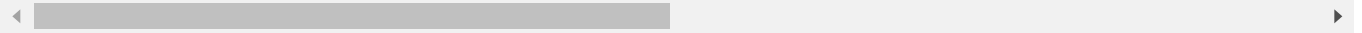
import datetime
import lightgbm as lgb
from scipy import stats
from sklearn.model_selection import train_test_split, StratifiedKFold, KFold, cross_val_score
from sklearn.preprocessing import StandardScaler
import os
import lightgbm as lgb
from sklearn.metrics import accuracy_score, roc_auc_score
from sklearn import metrics
from sklearn import linear_model
from tqdm import tqdm_notebook
from catboost import CatBoostClassifier
```

```
Requirement already satisfied: lightgbm in /usr/local/lib/python3.6/dist-packages (2.2.3)
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from lightgbm==2.2.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from lightgbm==2.2.3)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.6/dist-packages (from lightgbm==2.2.3)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from lightgbm==2.2.3)
Collecting catboost
  Downloading https://files.pythonhosted.org/packages/52/39/128fff65072c8327371e3c594f3c...
    |████████████████████| 66.2MB 61kB/s
Requirement already satisfied: graphviz in /usr/local/lib/python3.6/dist-packages (from catboost==0.18.1)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.6/dist-packages (from catboost==0.18.1)
```

```

Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from catboost)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.6/dist-packages (from catboost)
Requirement already satisfied: pandas>=0.24.0 in /usr/local/lib/python3.6/dist-packages (from catboost)
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from catboost)
Requirement already satisfied: plotly in /usr/local/lib/python3.6/dist-packages (from catboost)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packages (from catboost)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.6/dist-packages (from catboost)
Requirement already satisfied: cycycler>=0.10 in /usr/local/lib/python3.6/dist-packages (from catboost)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packages (from catboost)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from catboost)
Requirement already satisfied: retrying>=1.3.3 in /usr/local/lib/python3.6/dist-packages (from catboost)
Installing collected packages: catboost
Successfully installed catboost-0.24.2

```



```

from google.colab import drive
drive.mount('/content/drive')

```

Mounted at /content/drive

```

# sensor = pd.read_csv('../input/sensor.csv')
# sensor = pd.read_csv('../input/vombas/sensor_procesado.csv')
#sensor = pd.read_csv('dataset_sensor_procesado.csv')
#sensor = pd.read_csv('../input/bombas-sensores-conocidos/sensor2.csv')
#sensor = pd.read_csv('../input/28k-s24-balan-vombas/sensor2-ordenado_status_sin_broken_balan')
#sensor.drop(['Unnamed: 0'], axis=1, inplace=True)

sensor = pd.read_csv('/content/drive/My Drive/datasets/sensor2-ordenado_status_sin_broken_balan')

sensor.head()

```

```

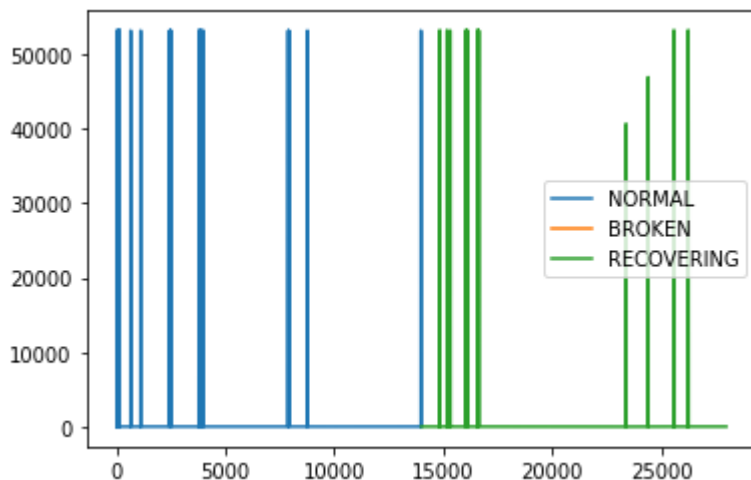
    Unnamed:  timestamp  sensor_00  sensor_01  sensor_02  sensor_03  sensor_04  sensor_05  sensor_06  sensor_07  sensor_08  sensor_09  sensor_10  sensor_11  sensor_12  sensor_13  sensor_14  sensor_15  sensor_16  sensor_17  sensor_18  sensor_19  sensor_20  sensor_21  sensor_22  sensor_23  sensor_24  sensor_25  sensor_26  sensor_27  sensor_28  sensor_29  sensor_30  sensor_31  sensor_32  sensor_33  sensor_34  sensor_35  sensor_36  sensor_37  sensor_38  sensor_39  sensor_40  sensor_41  sensor_42  sensor_43  sensor_44  sensor_45  sensor_46  sensor_47  sensor_48  sensor_49  sensor_50  sensor_51  sensor_52  sensor_53  sensor_54  sensor_55  sensor_56  sensor_57  sensor_58  sensor_59  sensor_60  sensor_61  sensor_62  sensor_63  sensor_64  sensor_65  sensor_66  sensor_67  sensor_68  sensor_69  sensor_70  sensor_71  sensor_72  sensor_73  sensor_74  sensor_75  sensor_76  sensor_77  sensor_78  sensor_79  sensor_80  sensor_81  sensor_82  sensor_83  sensor_84  sensor_85  sensor_86  sensor_87  sensor_88  sensor_89  sensor_90  sensor_91  sensor_92  sensor_93  sensor_94  sensor_95  sensor_96  sensor_97  sensor_98  sensor_99

#sensor.drop(['sensor_15'], axis=1, inplace=True)
sensor.drop(['timestamp'], axis=1, inplace=True)

# lineA DE LOS 22K INSTANCIAS
plt.plot(sensor.loc[sensor['machine_status'] == 'NORMAL', 'sensor_02'], label='NORMAL')
plt.plot(sensor.loc[sensor['machine_status'] == 'BROKEN', 'sensor_02'], label='BROKEN')
plt.plot(sensor.loc[sensor['machine_status'] == 'RECOVERING', 'sensor_02'], label='RECOVERING')
plt.legend()

```

<matplotlib.legend.Legend at 0x7f5d05b9b470>



```
cleanup_nums = {"machine_status": {"NORMAL": 0, "RECOVERING": 1, "BROKEN": 2}}
```

```

sensor.replace(cleanup_nums, inplace=True)
sensor.head(30)

```

	Unnamed: 0	sensor_00	sensor_01	sensor_02	sensor_03
0	0	2.465394	47.0920100000000002	53.2117999999999997	46.3107600000000002
1	1	2.465394	47.0920100000000002	53.2117999999999997	46.3107600000000002
2	2	2.444734	47.3524299999999998	53.2117999999999997	46.3975700000000002
3	3	2.460474	47.0920100000000002	53.1683999999999998	46.397567749023402
4	4	2.445718	47.1354100000000000	53.2117999999999997	46.397567749023402
5	5	2.453588	47.0920100000000002	53.1683999999999998	46.397567749023402
6	6	2.455556	47.0486099999999996	53.168399810790994	46.397567749023402
7	7	2.449653	47.1354100000000000	53.168399810790994	46.397567749023402
8	8	2.463426	47.0920100000000002	53.168399810790994	46.397567749023402
9	9	2.445718	47.1788200000000002	53.1683999999999998	46.397567749023402
10	10	2.464410	47.4826400000000004	53125.0000000000000000	46.397567749023402
11	11	2.444734	47.9166600000000000	53.1683999999999998	46.397567749023402
12	12	2.460474	48.2638900000000004	53125.0000000000000000	46.397567749023402
13	13	2.448669	48.4375000000000000	53.1683999999999998	46.397567749023402
14	14	2.453588	48.5677099999999998	53.1683999999999998	46.397567749023402
15	15	2.455556	48.3941000000000002	53125.0000000000000000	46.3975700000000002
16	16	2.449653	48.3941000000000002	53.1683999999999998	46.3107600000000002
17	17	2.463426	48.4808999999999998	53.6892400000000012	46.310760498046896
18	18	2.445718	48.6111099999999996	53125.0000000000000000	46.310760498046896
19	19	2.464410	48.6111099999999996	53.1683999999999998	46.310760498046896

```
for col in sensor.columns[1:-1]:
```

```
    sensor[col] = sensor[col].fillna(sensor[col].mean())
```

```
# bosque aleatorio
```

```
23      23      2.453588  49.0885400000000002      53.1683999999999998  46.267360687255895
```

```
sensor.fillna(sensor.mean(), inplace=True)
```

```
sensor.head()
```

	Unnamed: 0	sensor_00	sensor_01	sensor_02	sensor_03	
0	0	2.465394	47.092010000000002	53.211799999999997	46.310760000000002	6343
1	1	2.465394	47.092010000000002	53.211799999999997	46.310760000000002	6343
2	2	2.444734	47.352429999999998	53.211799999999997	46.397570000000002	6

```
print(sensor.shape)
```

```
(28002, 26)
```

```
# Encontrar características importantes en Scikit-learn
```

```
# from sklearn.ensemble import RandomForestClassifier
```

```
#Create a Gaussian Classifier
```

```
#clf=RandomForestClassifier(n_estimators=100)
```

```
#Train the model using the training sets y_pred=clf.predict(X_test)
```

```
#clf.fit(X_train,y_train)
```

```
# no correr
```

```
#import pandas as pd
```

```
#feature_imp = pd.Series(clf.feature_importances_,index=iris.feature_names).sort_values(ascen
```

```
#feature_imp = pd.Series(clf.feature_importances_,index=sensor.columns[19:27]).sort_values(as
```

```
#print(feature_imp)
```

```
#Visualización
```

```
#import matplotlib.pyplot as plt
```

```
#import seaborn as sns
```

```
##matplotlib inline
```

```
# Creating a bar plot
```

```
#sns.barplot(x=feature_imp, y=feature_imp.index)
```

```
# Add labels to your graph
```

```
#plt.xlabel('Feature Importance Score')
```

```
#plt.ylabel('Features')
```

```
#plt.title("Visualizing Important Features")
```

```
#plt.legend()
```

```
#plt.show()
```

```
X=sensor[['sensor_00', 'sensor_01', 'sensor_02', 'sensor_03','sensor_04', 'sensor_11', 'senso
```

```
#y=sensor['target'] # Labels
```

```
y=sensor['machine_status'] # Labels
```

```
# Split dataset into training set and test set
```

```
#X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3) # 70% training and
```

```

# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2) # 80% training and 20% test

from sklearn.ensemble import RandomForestClassifier

#Create a Random Forest Classifier
clf=RandomForestClassifier(n_estimators=500)

start = time.time()

#Train the model using the training sets y_pred=clf.predict(X_test)
clf.fit(X_train,y_train)

stop = time.time()
print(f"Training time: {stop - start}s")

y_pred=clf.predict(X_test)

#Import scikit-learn metrics module for accuracy calculation
from sklearn import metrics
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))

#predicciones del item 17156 q es 1
clf.predict([[0.0,53.55902,52.77777,43.402774810790994,204.72509765625,3.7302410000000004,404

    Training time: 13.407578945159912s
    Accuracy: 1.0
    array([1])

#predicciones
clf.predict([[0.0,53.55902,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]])

    array([1])

#predicciones
clf.predict([[0.0,53.55902,52.77777,43.402774810790994,204.72509765625,3.7302410000000004,404

    array([1])

# Extract single tree
estimator = clf.estimators_[5]

#from sklearn.tree import export_graphviz
# Export as dot file
#export_graphviz(estimator, out_file='tree.dot',
#
#    feature_names = ['sensor_00', 'sensor_01', 'sensor_02', 'sensor_03', 'sensor_04', 'sensor_05', 'sensor_06', 'sensor_07', 'sensor_08', 'sensor_09', 'sensor_10', 'sensor_11', 'sensor_12', 'sensor_13', 'sensor_14', 'sensor_15', 'sensor_16', 'sensor_17', 'sensor_18', 'sensor_19', 'sensor_20', 'sensor_21', 'sensor_22', 'sensor_23', 'sensor_24', 'sensor_25', 'sensor_26', 'sensor_27', 'sensor_28', 'sensor_29', 'sensor_30', 'sensor_31', 'sensor_32', 'sensor_33', 'sensor_34', 'sensor_35', 'sensor_36', 'sensor_37', 'sensor_38', 'sensor_39', 'sensor_40', 'sensor_41', 'sensor_42', 'sensor_43', 'sensor_44', 'sensor_45', 'sensor_46', 'sensor_47', 'sensor_48', 'sensor_49', 'sensor_50', 'sensor_51', 'sensor_52', 'sensor_53', 'sensor_54', 'sensor_55', 'sensor_56', 'sensor_57', 'sensor_58', 'sensor_59', 'sensor_60', 'sensor_61', 'sensor_62', 'sensor_63', 'sensor_64', 'sensor_65', 'sensor_66', 'sensor_67', 'sensor_68', 'sensor_69', 'sensor_70', 'sensor_71', 'sensor_72', 'sensor_73', 'sensor_74', 'sensor_75', 'sensor_76', 'sensor_77', 'sensor_78', 'sensor_79', 'sensor_80', 'sensor_81', 'sensor_82', 'sensor_83', 'sensor_84', 'sensor_85', 'sensor_86', 'sensor_87', 'sensor_88', 'sensor_89', 'sensor_90', 'sensor_91', 'sensor_92', 'sensor_93', 'sensor_94', 'sensor_95', 'sensor_96', 'sensor_97', 'sensor_98', 'sensor_99']

```

```

feature_names = [ 'sensor_00', 'sensor_01', 'sensor_02', 'sensor_03', 'sensor_04',
class_names = [ 'machine_status'],
# rounded = True, proportion = False,
# precision = 2, filled = True)

# validacion cruzada
# https://jamesrledoux.com/code/k\_fold\_cross\_validation

```

```
from sklearn.model_selection import cross_validate
```

```

start1 = time.time()
model = RandomForestClassifier(random_state=1)
cv = cross_validate(model, X, y, cv=10)
print(cv['test_score'])
print(cv['test_score'].mean())
stop1 = time.time()
print(f"Training time: {stop1 - start1}s")

```

```

[0.99464477 0.99964298 1.          1.          1.          1.
 1.          1.          1.          0.85642857]
0.9850716325802009
Training time: 28.07333517074585s

```

```
#https://stackoverflow.com/questions/20662023/save-python-random-forest-model-to-file
```

```

from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
from sklearn.metrics import plot_confusion_matrix

```

```

start1 = time.time()
#model = RandomForestClassifier(random_state=1)
model = RandomForestClassifier(n_estimators=500)

```

```

cv = cross_validate(model, X, y, cv=10)
print(confusion_matrix(y_test,y_pred))
print(cv['test_score'])
print(cv['test_score'].mean())
stop1 = time.time()
print(f"Training time: {stop1 - start1}s")

```

```

print(confusion_matrix(y_test,y_pred))
print(classification_report(y_test,y_pred))

```

```

#plot_confusion_matrix(clf, X_test, y_test)
# plot_confusion_matrix(clf, X_test, y_test)
plot_confusion_matrix(clf, X_test, y_test, cmap=plt.cm.Blues)

```

```
plt.show()
```

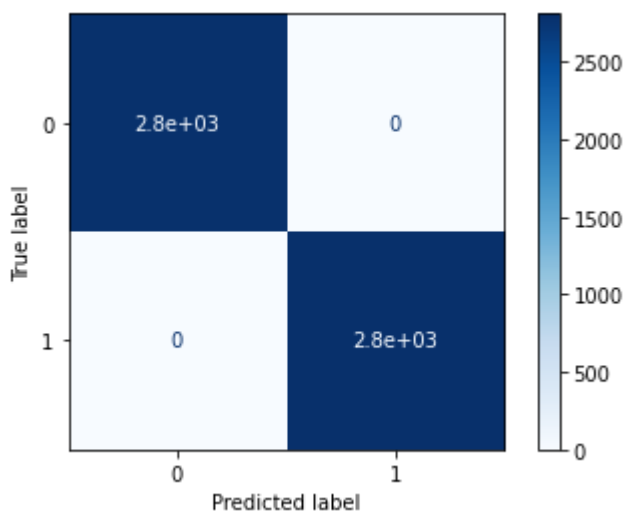
```
[[2792    0]
 [    0 2809]]
[0.99393074 0.99964298 1.          1.          1.          1.
 1.          1.          1.          0.88071429]
```

```
0.9874288009384402
```

```
Training time: 139.9744303226471s
```

```
[[2792    0]
 [    0 2809]]
```

		precision	recall	f1-score	support
	0	1.00	1.00	1.00	2792
	1	1.00	1.00	1.00	2809
accuracy				1.00	5601
macro avg		1.00	1.00	1.00	5601
weighted avg		1.00	1.00	1.00	5601



```
# version with multi scoring
```

```
from sklearn.metrics import classification_report, confusion_matrix
```

```
import matplotlib.pyplot as plt
```

```
from sklearn.metrics import plot_confusion_matrix
```

```
start1 = time.time()
```

```
#model = RandomForestClassifier(random_state=1)
```

```
model = RandomForestClassifier(n_estimators=500)
```

```
cv = cross_validate(model, X, y, cv=10)
```

```
#recall_score=cross_validation.cross_val_score(clf, X,y, cv=10, scoring ='recall')
```

```
#recall_score=cross_val_score(model, X,y, cv=10, scoring ='recall')
```

```
f1=cross_validate(model, X,y, cv=10, scoring ='f1')
```

```
recall_score=cross_validate(model, X,y, cv=10, scoring ='recall')
```

```
pre_score=cross_validate(model, X,y, cv=10, scoring ='precision_macro')
```

```
print(confusion_matrix(y_test,y_pred))
```

```
print(f"precision_macro_score:")
```

```
print(pre_score['test_score'])
```

```
print(pre_score['test_score'].mean())
```

```
print(f"test_score:")
```

```
print(cv['test_score'])
```



```
print(cv['test_score'].mean())
print(f"recall:")
print(recall_score['test_score'])
print(recall_score['test_score'].mean())
print(f"f1score:")
print(f1['test_score'])
print(f1['test_score'].mean())
stop1 = time.time()
print(f"Training time: {stop1 - start1}s")

print(confusion_matrix(y_test,y_pred))
print(classification_report(y_test,y_pred))

#plot_confusion_matrix(clf, X_test, y_test)
# plot_confusion_matrix(clf, X_test, y_test)
plot_confusion_matrix(clf, X_test, y_test, cmap=plt.cm.Blues)

plt.show()
```

```

[[2792    0]
 [    0 2809]]
precision_macro_score:
[0.9975142  0.99964311 1.          1.          1.          1.
 1.          1.          1.          0.92225241]
0.9919409723151702
test_score:
[0.99393074 0.99964298 1.          1.          1.          1.
 1.          1.          1.          0.88857143]
0.9882145152241545

```

```
# version with multi scoring mejorada
```

```
from sklearn.metrics import classification_report, confusion_matrix
```

```
import matplotlib.pyplot as plt
```

```
from sklearn.metrics import plot_confusion_matrix
```

```
start1 = time.time()
```

```
#model = RandomForestClassifier(random_state=1)
```

```
model = RandomForestClassifier(n_estimators=500)
```

```
#GH
```

```
model.fit(X_train,y_train)
```

```
y_pred=model.predict(X_test)
```

```
#GH
```

```
cv = cross_validate(model, X, y, cv=10)
```

```
#recall_score=cross_validation.cross_val_score(clf, X,y, cv=10, scoring = 'recall')
```

```
#recall_score=cross_val_score(model, X,y, cv=10, scoring = 'recall')
```

```
#scoring = ['neg_mean_absolute_error', 'r2']
```

```
scores=cross_validate(model, X,y, cv=10, scoring = ['accuracy','f1','recall','precision'],ret
```

```
#recall_score=cross_validate(model, X,y, cv=10, scoring = 'recall')
```

```
#pre_score=cross_validate(model, X,y, cv=10, scoring = 'precision_macro')
```

```
print(confusion_matrix(y_test,y_pred))
```

```
print(f"multi_metric_scores:")
```

```
#print(scores['test_score'])
```

```
print(scores)
```

```
#print(scores['test_score'].mean())
```

```
#print(scores.mean())
```

```
#print(f"precision_macro_score:")
```

```
#print(pre_score['test_score'])
```

```
#print(pre_score['test_score'].mean())
```

```
#print(f"test_score:")
```

```
#print(cv['test_score'])
```

```
#print(cv['test_score'].mean())
```

```
#print(f"recall:")
```

```
#print(recall_score['test_score'])
```

```
#print(recall_score['test_score'].mean())

#print(f"f1score:")
#print(f1['test_score'])
#print(f1['test_score'].mean())

stop1 = time.time()
print(f"Training time: {stop1 - start1}s")

print(confusion_matrix(y_test,y_pred))
print(classification_report(y_test,y_pred))

#plot_confusion_matrix(clf, X_test, y_test)
# plot_confusion_matrix(clf, X_test, y_test)
plot_confusion_matrix(clf, X_test, y_test, cmap=plt.cm.Blues)

plt.show()

gh4 = scores.get("test_accuracy")

print(f"accuracy:")
print(gh4)
print(gh4.mean())

gh3 = scores.get("test_precision")

print(f"precision:")
print(gh3)
print(gh3.mean())

gh = scores.get("test_recall")

print(f"recall:")
print(gh)
print(gh.mean())

gh2 = scores.get("test_f1")

print(f"f1:")
print(gh2)
print(gh2.mean())

CM = confusion_matrix(y_test, y_pred)
print(f"-----")
print(f"matriz de confusion:")
TN = CM[0][0]
FN = CM[1][0]
TP = CM[1][1]
FP = CM[0][1]
print(f"TN={TN}, FP={FP} ")
print(f"FN={FN}, TP={TP} ")
```

```
print(f"-----")
print(f"matriz de confusion %:")
total1=(TN+TP+FN+FP)

print(f"TN={100*TN/total1}, FP={100*FP/total1} ")
print(f"FN={100*FN/total1}, TP={100*TP/total1} ")

print(f"-----")
acc1=(TN+TP)/(TN+TP+FN+FP)
print(f"accuracy1={acc1}")

print(f"-----")
re1=(TP)/(TP+FN)
print(f"reca1={re1}")

print(f"-----")
pre1=(TP)/(TP+FP)
print(f"pre1={pre1}")

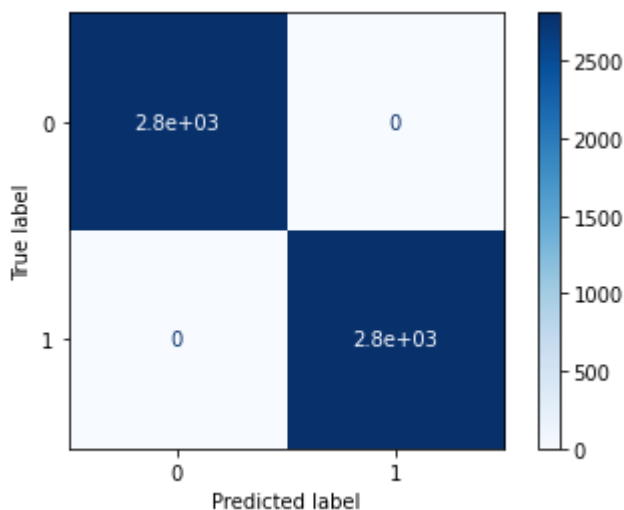
print(f"-----")
f1s1=(2*pre1*re1)/(pre1+re1)
print(f"f1score={f1s1}")
```



```
[[2792      0]
 [    0 2809]]
multi_metric_scores:
{'fit_time': array([13.70309615, 13.68394828, 13.90837884, 13.79051661, 13.67019773,
14.14955759, 14.21738338, 14.35204458, 14.29634309, 13.40078807]), 'score_time':
0.11818528, 0.12190866, 0.12092113, 0.12525129, 0.11808348]), 'test_accuracy': ar
1.          , 1.          , 1.          , 1.          , 0.82964286]), 'test_f1': array([0.
1.          , 1.          , 1.          , 1.          , 0.85426214]), 'test_recall': arra
1.          , 1.          , 1.          , 1.          , 0.99857143]), 'test_precision': a
1.          , 1.          , 1.          , 1.          , 0.74639616])}}
```

Training time: 295.0970540046692s

[[2792 0] [0 2809]]		precision	recall	f1-score	support
	0	1.00	1.00	1.00	2792
	1	1.00	1.00	1.00	2809
accuracy				1.00	5601
macro avg		1.00	1.00	1.00	5601
weighted avg		1.00	1.00	1.00	5601



```
accuracy:
50.00000000 0.00000000 1.00000000 1.00000000
```

```
import joblib
from sklearn.ensemble import RandomForestClassifier
# create RF
```

1 1 1 0 716396161

```
# save
joblib.dump(clf, "my_random_forest.joblib")
```

```
['my random forest.joblib']
```

f1:

```
# load
loaded_rf = joblib.load("my_random_forest.joblib")
```

```
#predicciones
#clf.predict([[0.0,53.55902,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]])
```

```

#predicciones
loaded_rf.predict([[0.0,53.55902,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]])

        array([1])

# 1 es recovering
loaded_rf.predict([[0.0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]])

        array([1])

# 0 es recovering
loaded_rf.predict([[2.465394,47.092009999999995,53.2118,46.310759999999995,634375,47.52422,41

        array([1])

# 2 es broken
loaded_rf.predict([[2.258796,47.26563,52.73437,43.4461784362793,200.11573791503898,43.62322,4

        array([1])

# https://seaborn.pydata.org/generated/seaborn.barplot.html

import pandas as pd
#feature_imp = pd.Series(clf.feature_importances_,index=iris.feature_names).sort_values(ascen
#feature_imp = pd.Series(clf.feature_importances_,index=X.columns[1:8]).sort_values(ascending
feature_imp = pd.Series(clf.feature_importances_,index=X.columns[0:24]).sort_values(ascending
print(feature_imp)

#Visualización
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
# Creating a bar plot
sns.barplot(x=feature_imp, y=feature_imp.index)
# Add labels to your graph
#plt.xlabel('Feature Importance Score')
plt.xlabel('Score de Caracteristicas importantes')
#plt.ylabel('Features')
plt.ylabel('Caracteristicas')
#plt.title("Visualizing Important Features")
plt.title("Visualización de carasteristicas importantes")
plt.legend()
plt.show()

#plt.savefig('destination_path.eps', format='eps' , dpi=1000)

plt.savefig('myimage.svg', format='svg', dpi=1200)

```

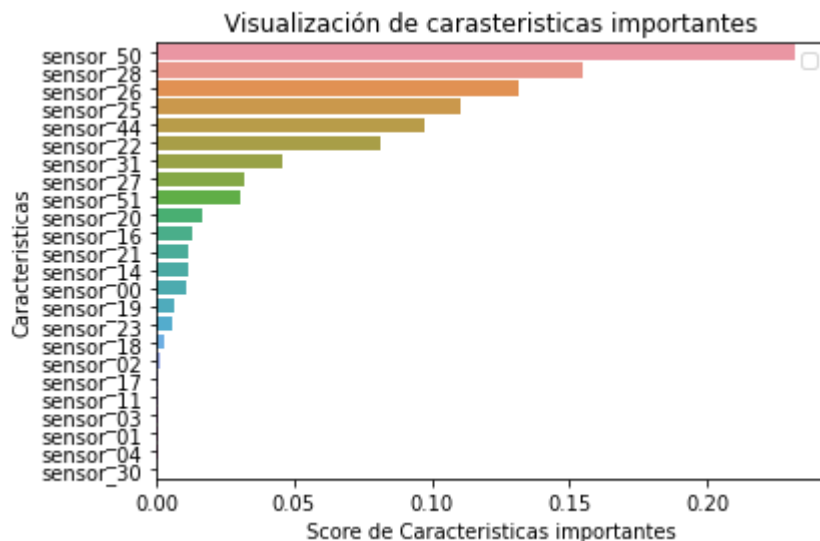
No handles with labels found to put in legend.

```

sensor_50    0.232008614527387
sensor_28    0.155139301713169
sensor_26    0.131795898646431
sensor_25    0.110861851269088
sensor_44    0.097505361456306
sensor_22    0.081278757345340
sensor_31    0.045465172383412
sensor_27    0.031709722277840
sensor_51    0.030814483227659
sensor_20    0.016924944332720
sensor_16    0.013014833663071
sensor_21    0.011633081219379
sensor_14    0.011314503461296
sensor_00    0.010804480943123
sensor_19    0.006824543819885
sensor_23    0.005805154043774
sensor_18    0.003030557161612
sensor_02    0.001205321192704
sensor_17    0.000589871703175
sensor_11    0.000555745724755
sensor_03    0.000537576783007
sensor_01    0.000515291133954
sensor_04    0.000410336591203
sensor_30    0.000254595379709

```

dtype: float64



<https://towardsdatascience.com/how-to-visualize-a-decision-tree-from-a-random-forest-in-pyt>