Non-Linear Model 2 - Random Forest

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sn
import pandas as pd
# Extra imports
from pandas import read_csv
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
import graphviz
from sklearn.tree import export_graphviz
from sklearn.metrics import confusion_matrix,\
        accuracy_score, classification_report, f1_score
from imblearn.under_sampling import RandomUnderSampler
from auxiliars import *
import pickle
```

In [39]:
```
np.random.seed(543)
```

Data

Data loading. In Random Forests it is not necessary to use standarized data.

In [40]:
```
data = pd.read_csv("./data/HTRU2/HTRU_2.csv", names = ['Profile_mea
n', 'Profile_stdev', 'Profile_skewness',
                                                       'Profile_kurt
osis', 'DM_mean', 'DM_stdev', 'DM_skewness',
                                                       'DM_kurtosis'
, 'Class'])
```

We split a separate test set of relative size 20%:

In [41]:
```
X_train, X_test, y_train, y_test = train_test_split(data[data.colum
ns[0:8]],
                                                    data['Class'],
                                                    test_size = 0.2
,
                                                    random_state =
543)
```

I order to improve the performance of Random Forest, we will also analyze the performance of the method with no-correlated data:

In [42]:
```
df = pd.DataFrame(data, columns = data.columns[:-1])
corrDf = df.corr()

features = np.full((corrDf.shape[0],), True, dtype=bool)
for i in range(corrDf.shape[0]):
    for j in range(i+1, corrDf.shape[0]):
        if corrDf.iloc[i,j] >= 0.9:
            if features[j]:
                features[j] = False

selectedFeatures = df.columns[features]

noCorrData = df[selectedFeatures]
noCorrData = pd.concat([noCorrData, data[['Class']]], axis = 1)
```

In [43]:
```
X_train_NC, X_test_NC, y_train_NC, y_test_NC = train_test_split(noC
orrData[noCorrData.columns[0:6]],
                                                                noCorrData['Cla
ss'],
                                                                test_size = 0.2
)
```

Model Training

Scikit-learn library offersa method for Random Forest classification.

In [44]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.utils.class_weight import compute_class_weight
```

We will use Random Forests with classes weights calculated.

In [59]:
```
y = data['Class'].tolist()
classes=[0,1]
cw = compute_class_weight('balanced', classes, y)
class_weight = dict(zip(classes, cw))

RF = RandomForestClassifier(oob_score=True, n_jobs = -1, class_weig
ht = class_weight)
class_weight
```

Out[59]:
```
{0: 0.550402853804047, 1: 5.460036607687615}
```

The only parameter we will hypertune is *n_estimators*, which indicates the number of trees of decision generated by the random forest.

In order to hypertune this parameter, we will loop through a list of different number of trees and save the results of each RF in order to see which one gives the lowest OOB score.

In [102]:
```
def optimize_ntrees(X_train, y_train, ntrees):
    rf_results= []
    for nt in ntrees:
        RF = RandomForestClassifier(n_estimators=nt,
                                                oob_score=True,
                                                n_jobs = -1,
                                                class_weight = class_
weight);
        model = RF.fit(X_train, y_train)
        rf_results.append(1-model.oob_score_)

    rf_results = pd.DataFrame({'ntrees':ntrees, 'OOB':rf_results})
    return rf_results
```

Normal Data Training

Let's train the model with tha normal data

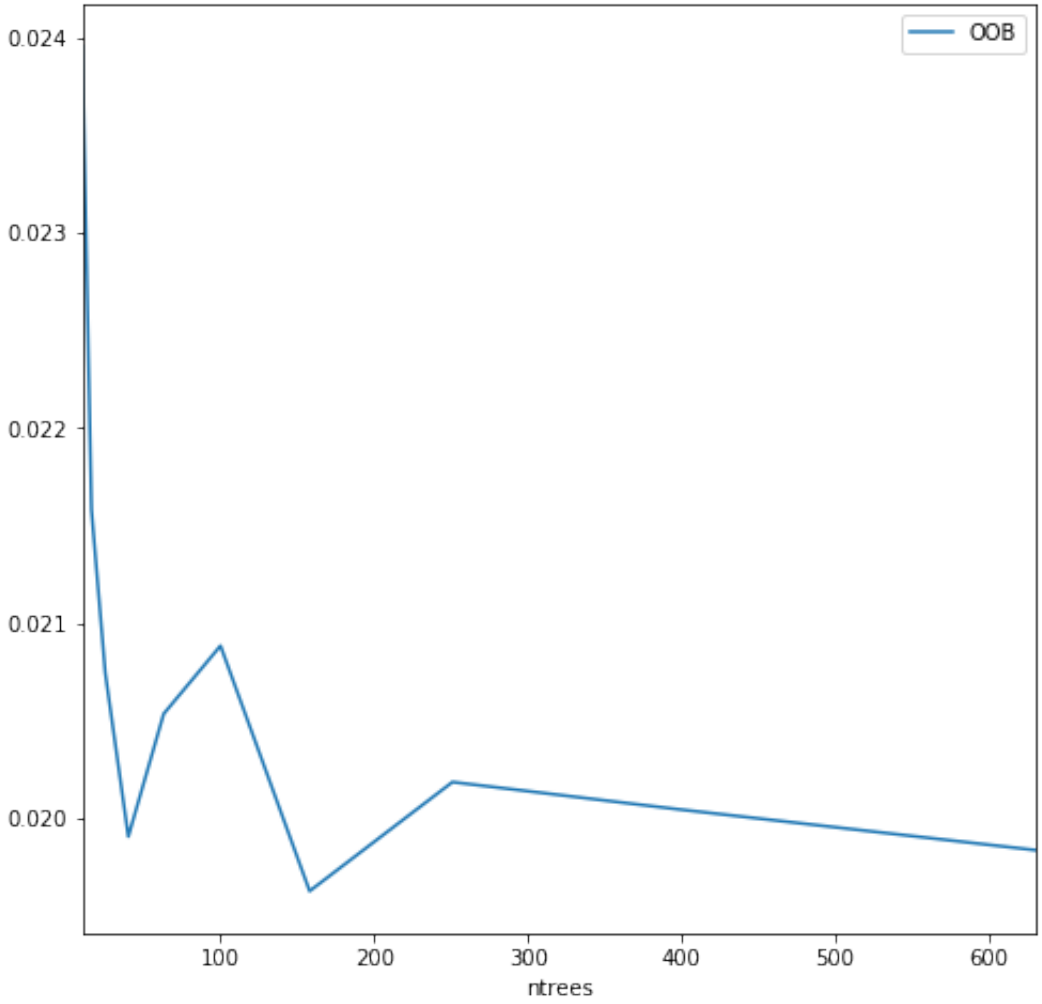
In [82]:
```
ntrees = np.array(np.round(10**np.arange(1,3,0.2)),dtype=int)
rf_results = optimize_ntrees(X_train, y_train, ntrees)
```

```
/home/ferja/.local/lib/python3.7/site-packages/sklearn/ensemble/_f
orest.py:523: UserWarning: Some inputs do not have OOB scores. Thi
s probably means too few trees were used to compute any reliable o
ob estimates.
  warn("Some inputs do not have OOB scores. "
/home/ferja/.local/lib/python3.7/site-packages/sklearn/ensemble/_f
orest.py:528: RuntimeWarning: invalid value encountered in true_di
vide
  predictions[k].sum(axis=1)[:, np.newaxis])
/home/ferja/.local/lib/python3.7/site-packages/sklearn/ensemble/_f
orest.py:523: UserWarning: Some inputs do not have OOB scores. Thi
s probably means too few trees were used to compute any reliable o
ob estimates.
  warn("Some inputs do not have OOB scores. "
/home/ferja/.local/lib/python3.7/site-packages/sklearn/ensemble/_f
orest.py:528: RuntimeWarning: invalid value encountered in true_di
vide
  predictions[k].sum(axis=1)[:, np.newaxis])
```

In [84]:
```
rf_results.plot(x='ntrees',y='OOB',figsize=(8,8));
rf_results
```

Out[84]:

	ntrees	OOB
0	10	0.023956
1	16	0.021581
2	25	0.020743
3	40	0.019905
4	63	0.020534
5	100	0.020883
6	158	0.019626
7	251	0.020184
8	398	0.020045
9	631	0.019835

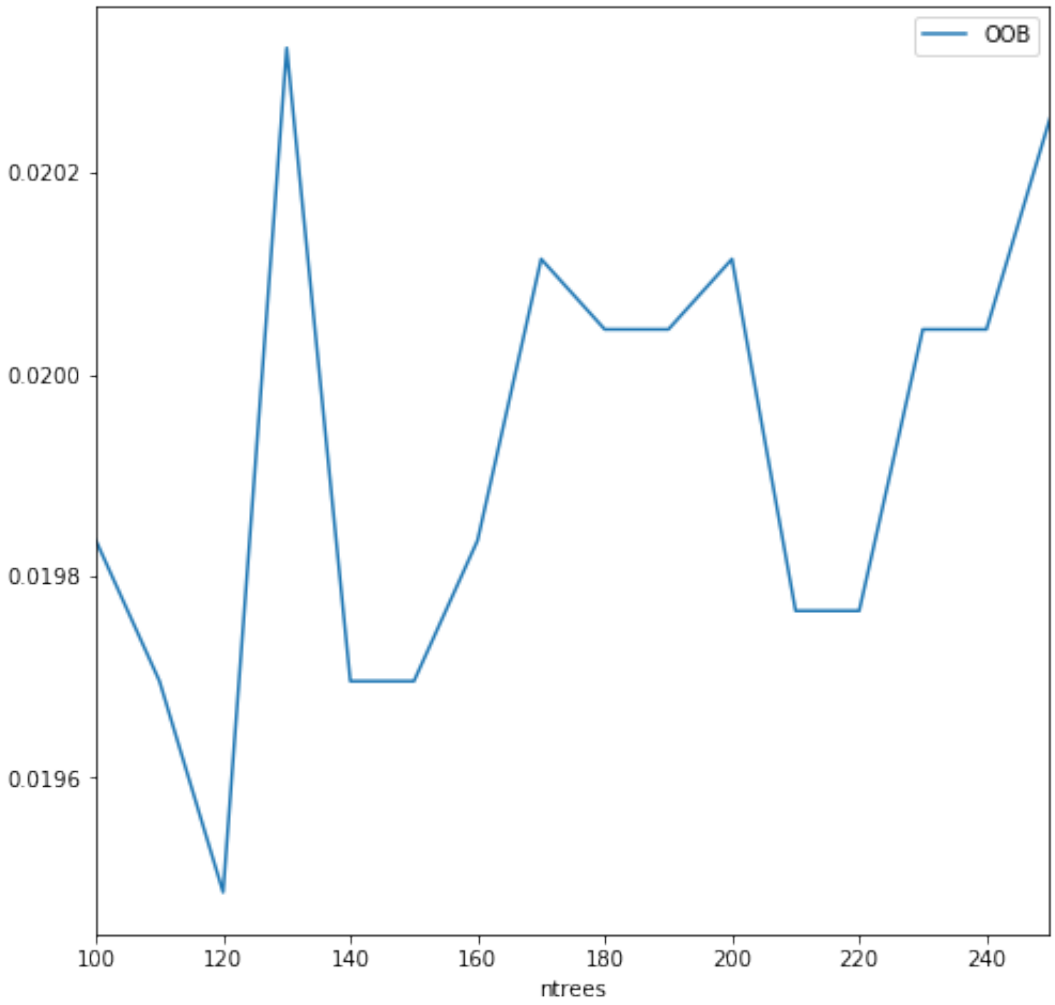


We see that the best number of trees is approximately between 100 and 250, let's try with values in that range

In [87]:
```
ntrees = np.array(range(10, 26))*10
rf_results = optimize_ntrees(X_train, y_train, ntrees)
rf_results.plot(x='ntrees',y='OOB',figsize=(8,8));
rf_results
```

Out[87]:

	ntrees	OOB
0	100	0.019835
1	110	0.019695
2	120	0.019486
3	130	0.020324
4	140	0.019695
5	150	0.019695
6	160	0.019835
7	170	0.020115
8	180	0.020045
9	190	0.020045
10	200	0.020115
11	210	0.019765
12	220	0.019765
13	230	0.020045
14	240	0.020045
15	250	0.020254




```
In [88]: rf_results.loc[rf_results.OOB.idxmin]
```

```
Out[88]: ntrees    120.000000
         OOB         0.019486
         Name: 2, dtype: float64
```

In [96]:
```
RF = RandomForestClassifier(n_estimators=rf_results.ntrees.loc[rf_r
esults.OOB.idxmin],
                                                    oob_score=True,
                                                    n_jobs = -1,
                                                    class_weight = class_weig
ht);

best_model = RF.fit(X_train, y_train)

y_pred = best_model.predict(X_train)

print("Training Error:")
print((1-accuracy_score(y_train, y_pred))*100)

confusionMatrix(y_train, y_pred, classes = [0,1])
```

```
Training Error:
0.006984215672578564
```

Out[96]:

Predicted	0	1
Real		
0	13020	0
1	1	1297

In [97]:
```
# Save model
RFFile = open('./models/RF_Best_Data_pickle_file', 'wb')
pickle.dump(best_model, RFFile)
```

No-correlated Data Training

Now with no-correlated data

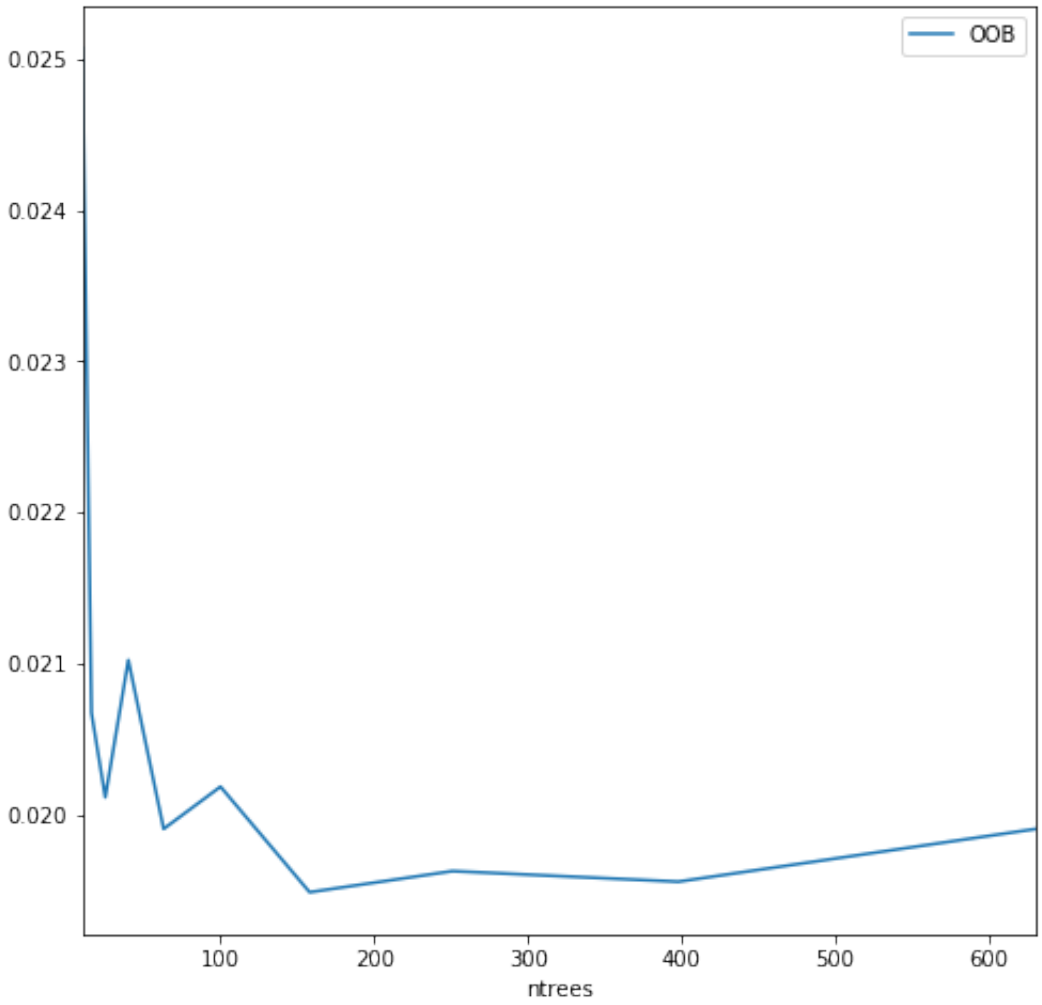
In [103]:
```
ntrees = np.array(np.round(10**np.arange(1,3,0.2)),dtype=int)
rf_results = optimize_ntrees(X_train_NC, y_train_NC, ntrees)
```

```
/home/ferja/.local/lib/python3.7/site-packages/sklearn/ensemble/_f
orest.py:523: UserWarning: Some inputs do not have OOB scores. Thi
s probably means too few trees were used to compute any reliable o
ob estimates.
  warn("Some inputs do not have OOB scores. "
/home/ferja/.local/lib/python3.7/site-packages/sklearn/ensemble/_f
orest.py:528: RuntimeWarning: invalid value encountered in true_di
vide
  predictions[k].sum(axis=1)[:, np.newaxis])
/home/ferja/.local/lib/python3.7/site-packages/sklearn/ensemble/_f
orest.py:523: UserWarning: Some inputs do not have OOB scores. Thi
s probably means too few trees were used to compute any reliable o
ob estimates.
  warn("Some inputs do not have OOB scores. "
/home/ferja/.local/lib/python3.7/site-packages/sklearn/ensemble/_f
orest.py:528: RuntimeWarning: invalid value encountered in true_di
vide
  predictions[k].sum(axis=1)[:, np.newaxis])
```

In [104]:
```
rf_results.plot(x='ntrees',y='OOB',figsize=(8,8));
rf_results
```

Out[104]:

	ntrees	OOB
0	10	0.025073
1	16	0.020673
2	25	0.020115
3	40	0.021022
4	63	0.019905
5	100	0.020184
6	158	0.019486
7	251	0.019626
8	398	0.019556
9	631	0.019905

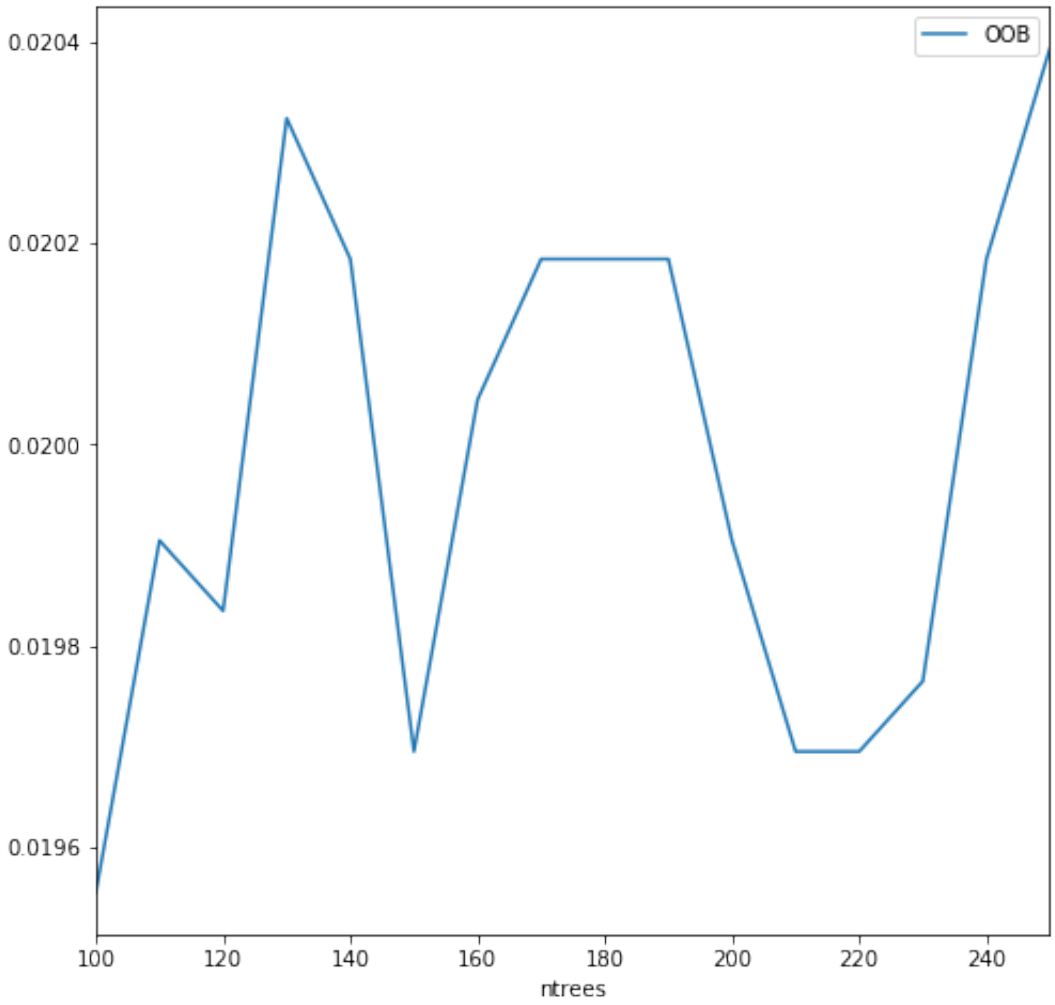


We see that the best number of trees is approximately between 100 and 250, let's try with values in that range

In [106]:
```
ntrees = np.array(range(10, 26))*10
rf_results = optimize_ntrees(X_train_NC, y_train_NC, ntrees)
rf_results.plot(x='ntrees',y='OOB',figsize=(8,8));
rf_results
```

Out[106]:

	ntrees	OOB
0	100	0.019556
1	110	0.019905
2	120	0.019835
3	130	0.020324
4	140	0.020184
5	150	0.019695
6	160	0.020045
7	170	0.020184
8	180	0.020184
9	190	0.020184
10	200	0.019905
11	210	0.019695
12	220	0.019695
13	230	0.019765
14	240	0.020184
15	250	0.020394




```
In [107]: rf_results.loc[rf_results.OOB.idxmin]
```

```
Out[107]: ntrees    100.000000
          OOB         0.019556
          Name: 0, dtype: float64
```

In [110]:
```
RF = RandomForestClassifier(n_estimators=rf_results.ntrees.loc[rf_r
esults.OOB.idxmin],
                                                    oob_score=True,
                                                    n_jobs = -1,
                                                    class_weight = class_weig
ht);

best_model_NC = RF.fit(X_train_NC, y_train_NC)

y_pred_NC = best_model_NC.predict(X_train_NC)

print("Training Error:")
print((1-accuracy_score(y_train_NC, y_pred_NC))*100)

confusionMatrix(y_train_NC, y_pred_NC, classes = [0,1])
```

```
Training Error:
0.006984215672578564
```

Out[110]:

Predicted	0	1
Real		
0	13020	0
1	1	1297

In [115]:
```
# Save model
RFFileNC = open('./models/RF_Best_Data_NC_pickle_file', 'wb')
pickle.dump(best_model_NC, RFFileNC)
```

Testing

Normal Data Model Testing

In [98]:
```
y_pred = best_model.predict(X_test)
confusionMatrix(y_test, y_pred, classes = [0,1])
```

Out[98]:

Predicted	0	1
Real		
0	3210	29
1	56	285

In [99]:
```
print(classification_report(y_test, y_pred, target_names=['no', 'ye
s']))
```

```
              precision    recall  f1-score   support

          no       0.98      0.99      0.99      3239
         yes       0.91      0.84      0.87       341

    accuracy                           0.98      3580
   macro avg       0.95      0.91      0.93      3580
weighted avg       0.98      0.98      0.98      3580
```

In [100]:
```
print("Testing Error:")
print((1-accuracy_score(y_test, y_pred))*100)
```

```
Testing Error:
2.3743016759776525
```

No-correlated Data Model Testing

In [112]:
```
y_pred_NC = best_model_NC.predict(X_test_NC)
confusionMatrix(y_test_NC, y_pred_NC, classes = [0,1])
```

Out[112]:

Predicted	0	1
Real		
0	3207	32
1	55	286

In [113]:
```
print(classification_report(y_test_NC, y_pred_NC, target_names=['no
', 'yes']))
```

```
              precision    recall  f1-score   support

          no       0.98      0.99      0.99      3239
         yes       0.90      0.84      0.87       341

    accuracy                           0.98      3580
   macro avg       0.94      0.91      0.93      3580
weighted avg       0.98      0.98      0.98      3580
```

In [114]:
```
print("Testing Error:")
print((1-accuracy_score(y_test_NC, y_pred_NC))*100)
```

```
Testing Error:
2.4301675977653647
```