renduLab1

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1 Lab 1 Evaluation

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In the following, we consider the (binarized) Compas dataset that we studied in the Lab

[9]:
```
from sklearn import tree
from matplotlib import pyplot as plt # for a good visualization of the trees

import csv
import numpy as np
from utils import load_from_csv

from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix
```

[10]:
```
train_examples, train_labels, features, prediction = load_from_csv("./compass.
↪csv")
print (train_examples)
print(train_labels
)
```

```
[[1 0 0 … 0 0 0]
 [1 0 1 … 0 0 0]
 [1 0 0 … 0 0 0]
 …
 [1 0 0 … 0 0 0]
 [1 0 0 … 0 0 0]
 [0 1 0 … 0 0 0]]
[1 0 0 … 1 0 1]
```

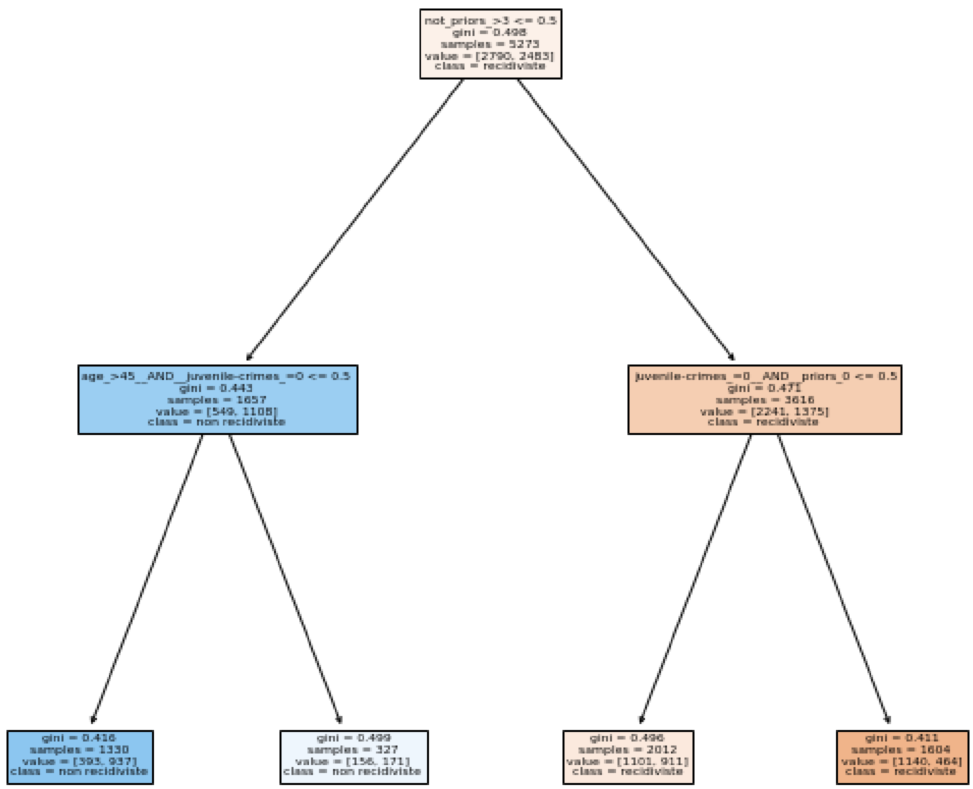
A decision tree configuration is a set of parameters that one can use to build decision trees. Propose 6 configurations that are likely to provide different topologies and caracteristics

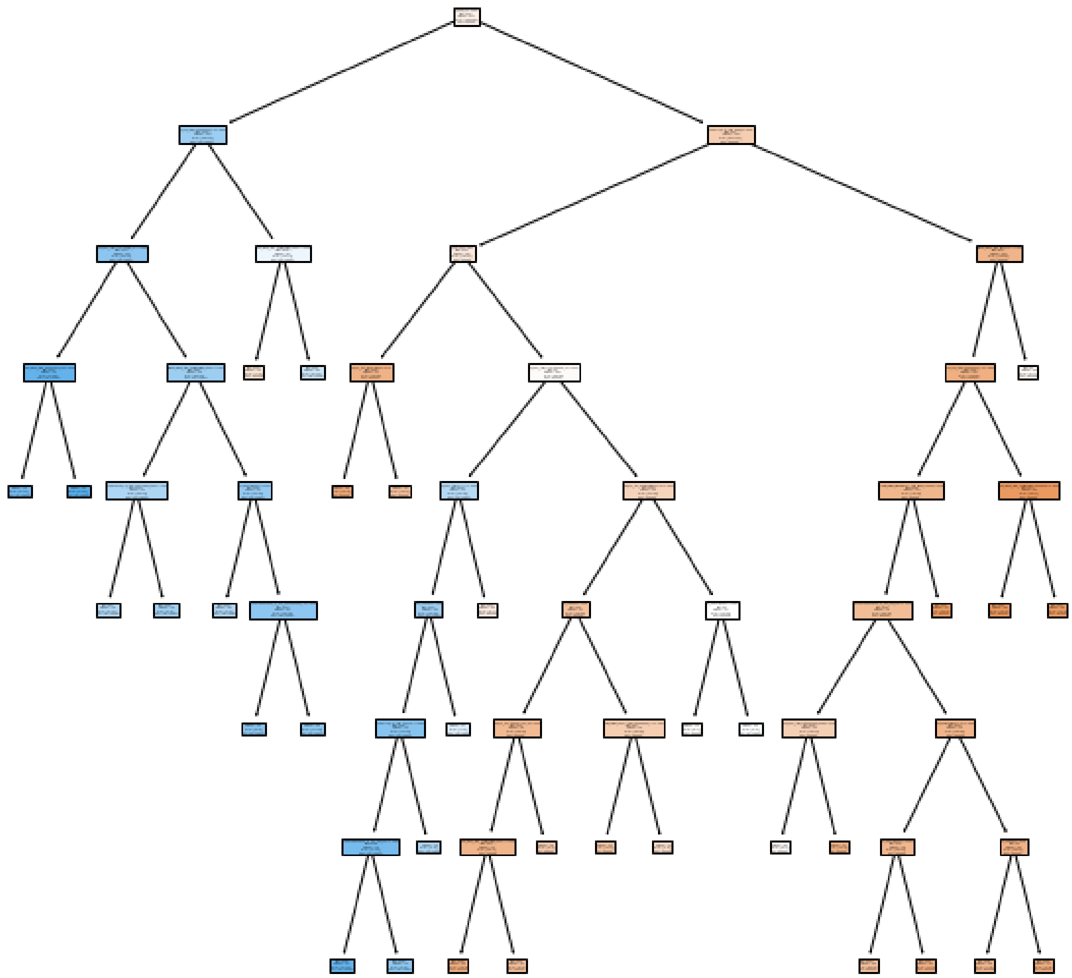
[11]:
```
treesParmeters = [
    #expected topologie and caracteristic
```

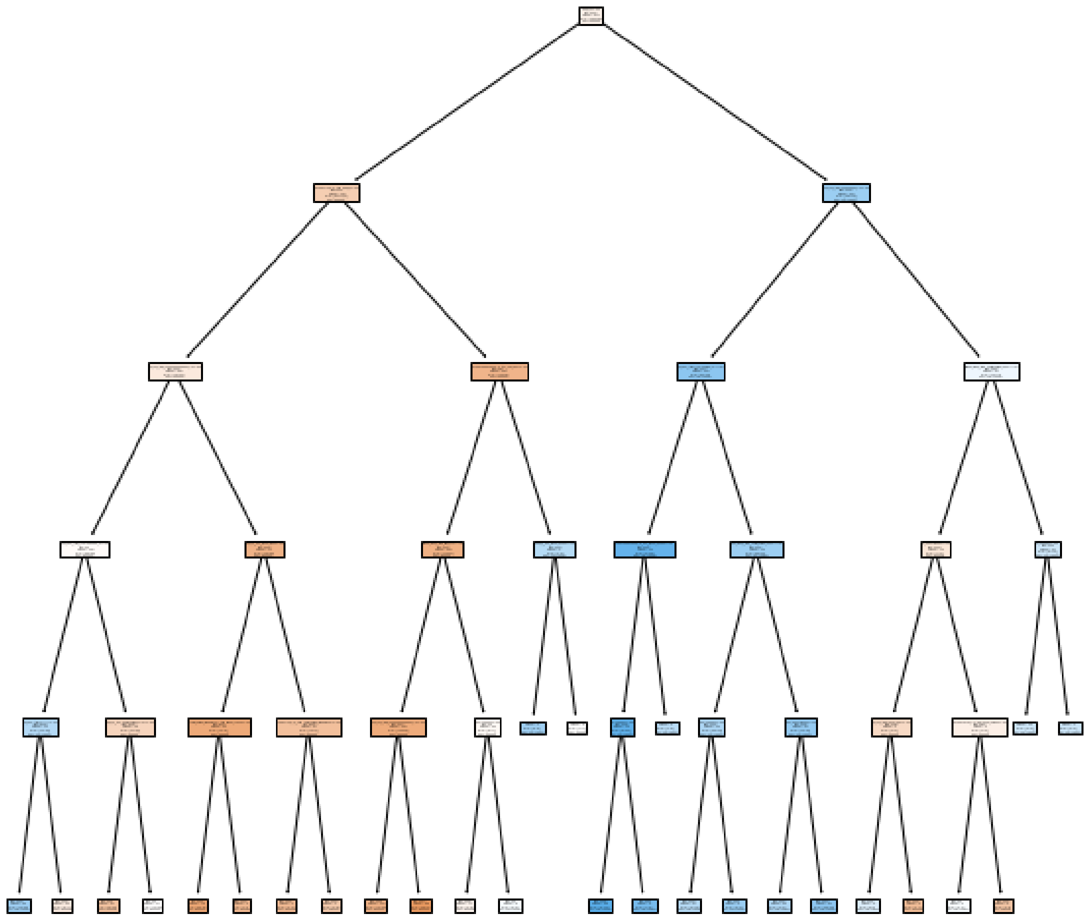
```
    {'splitter':'best', 'max_depth': 2, 'min_samples_leaf': 1},
    #expected topologie and caracteristic
    {'splitter':'random', 'max_depth': 10, 'min_samples_leaf': 100},
    #expected topologie and caracteristic
    {'splitter':'best', 'max_depth': 5, 'min_samples_leaf': 20},
    #expected topologie and caracteristic
    {'splitter':'best', 'max_depth': 5, 'min_samples_leaf':5},
    #expected topologie and caracteristic
    {'splitter':'best', 'max_depth': 100, 'min_samples_leaf':60},
    #expected topologie and caracteristic
    {'splitter':'best', 'max_depth': 100, 'min_samples_leaf':60},
]
nbTree = len(treesParmeters)
```

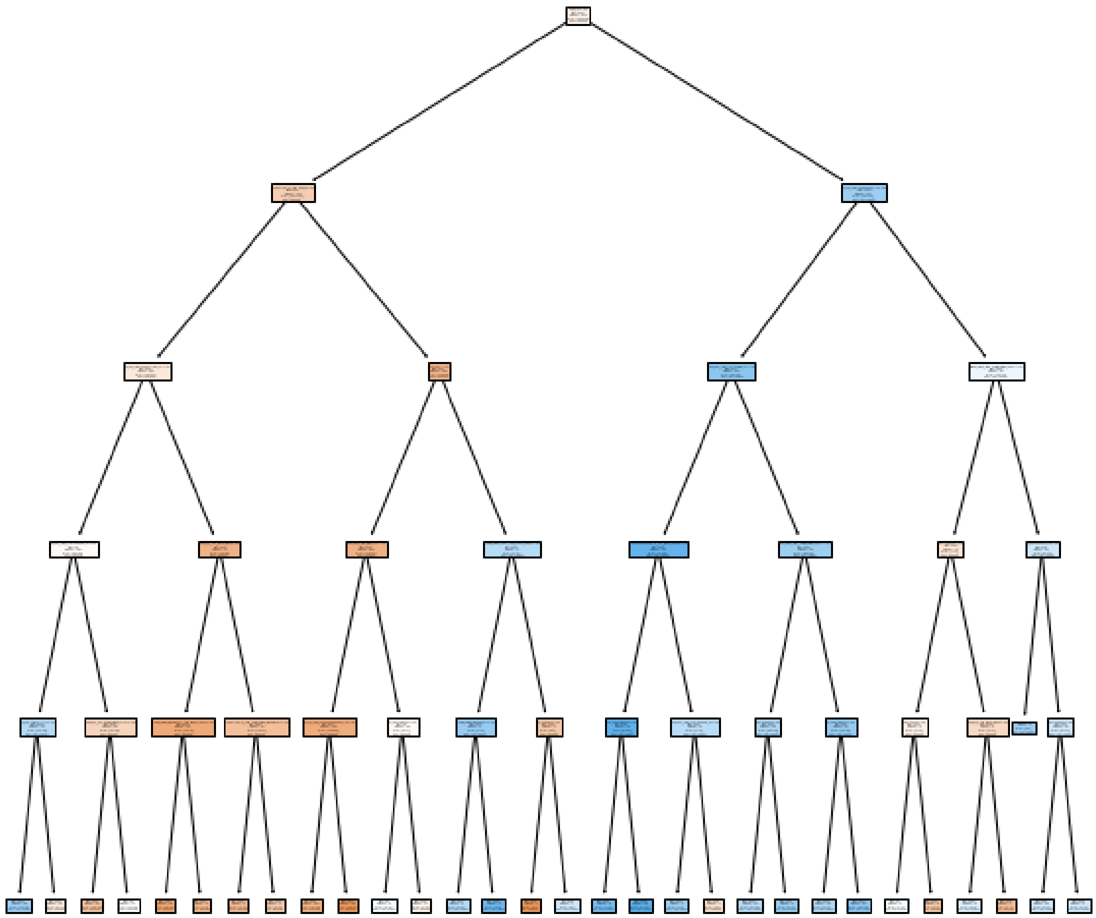
Train a decision tree for each of the previous configurations on the full dataset

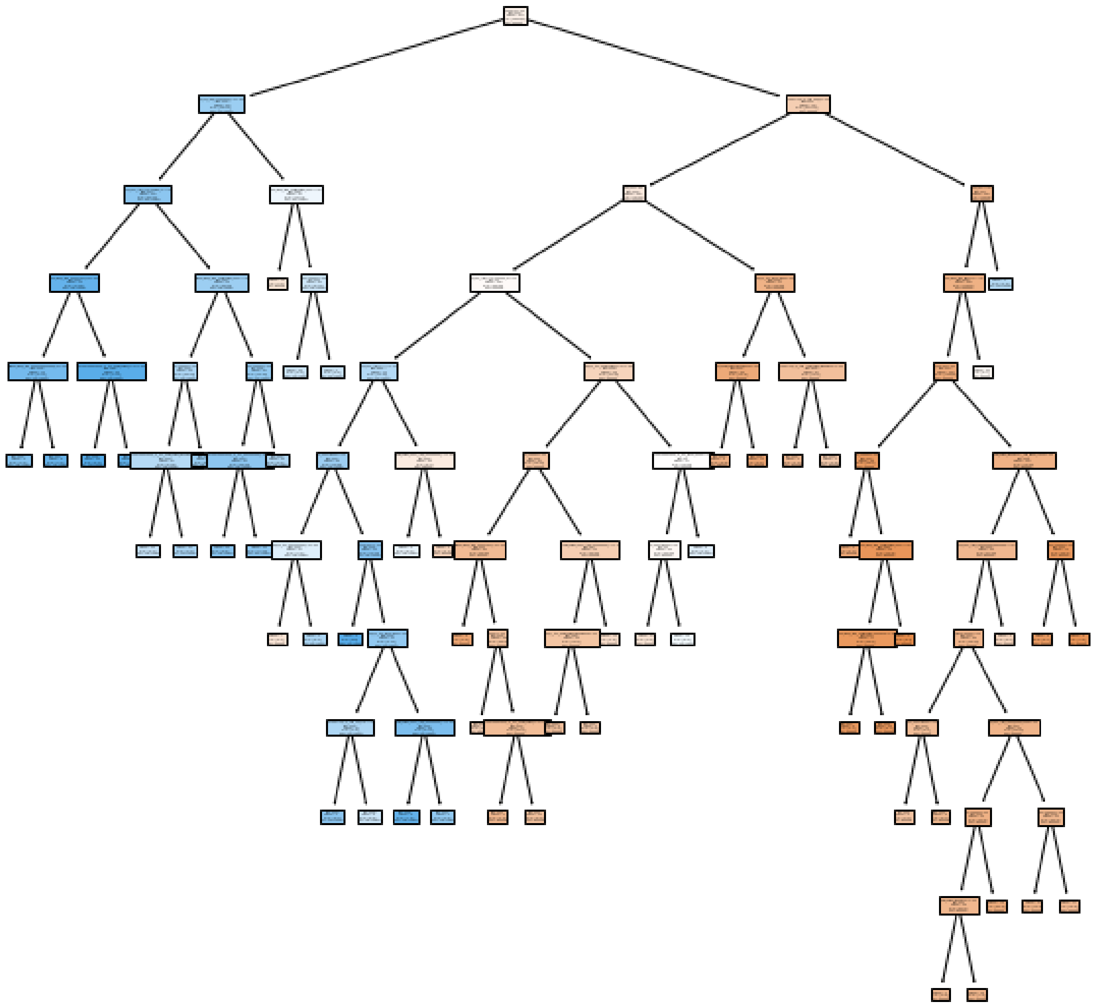
[12]:
```
for i in range (nbTree) :
    parameters= treesParmeters[i]
    clf = tree.DecisionTreeClassifier(
        splitter=parameters['splitter'],
        max_depth =parameters['max_depth'],
        min_samples_leaf =parameters['min_samples_leaf']
    )
    clf = clf.fit(train_examples, train_labels)

    plt.figure(figsize=(10,10))
    tree.plot_tree(clf,
                   feature_names= (features),
                   class_names= ("recidiviste", "non recidiviste"),
                   filled=True)
    plt.show()
```

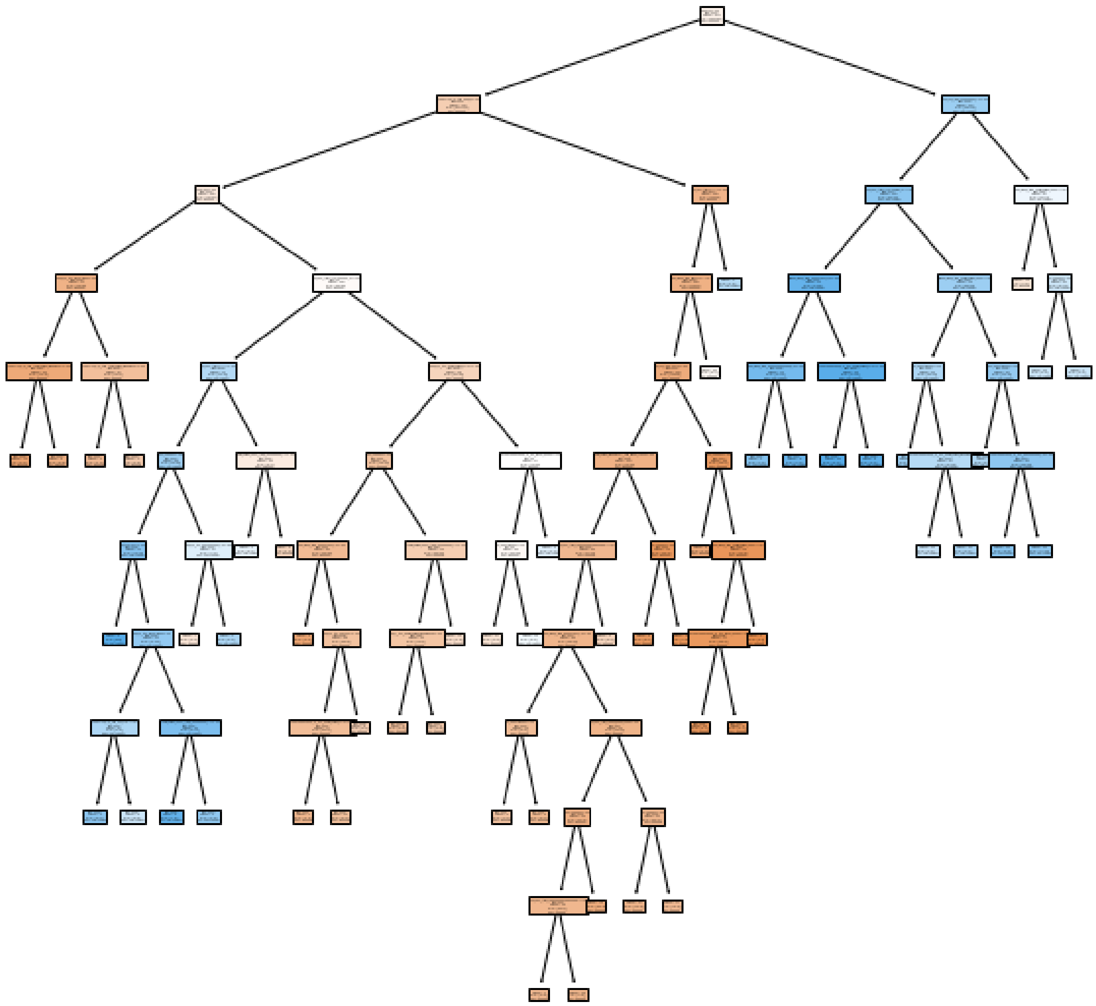

not_priors_>3 <= 0.5
gini = 0.498
samples = 5273
value = [2790, 2483]
class = recidiviste
age_>45__AND__juvenile-crimes_=0 <= 0.5
gini = 0.443
samples = 1657
value = [549, 1108]
class = non recidiviste
juvenile-crimes_=0__AND__priors_0 <= 0.5
gini = 0.471
samples = 3616
value = [2241, 1375]
class = recidiviste
gini = 0.416
samples = 1330
value = [393, 937]
class = non recidiviste
gini = 0.499
samples = 327
value = [156, 171]
class = non recidiviste
gini = 0.496
samples = 2012
value = [1101, 911]
class = recidiviste
gini = 0.411
samples = 1604
value = [1140, 464]
class = recidiviste











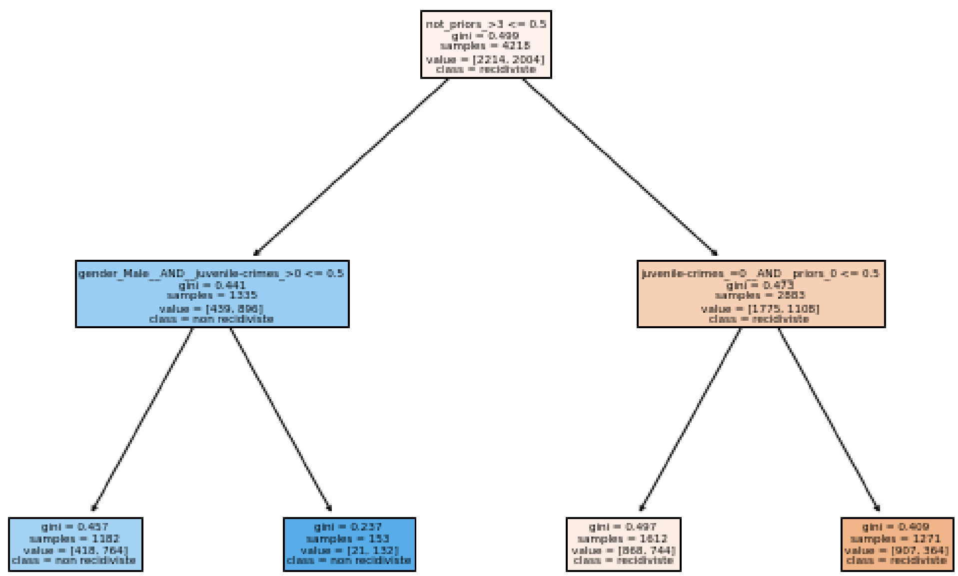
Propose an evaluation in terms of training and testing accuracies using 5-cross validation on two decision trees that have different typologies

[13]:
```
# We only keep the two first topologies
treesParmeters = treesParmeters[:2]
nbTree = len(treesParmeters)
```

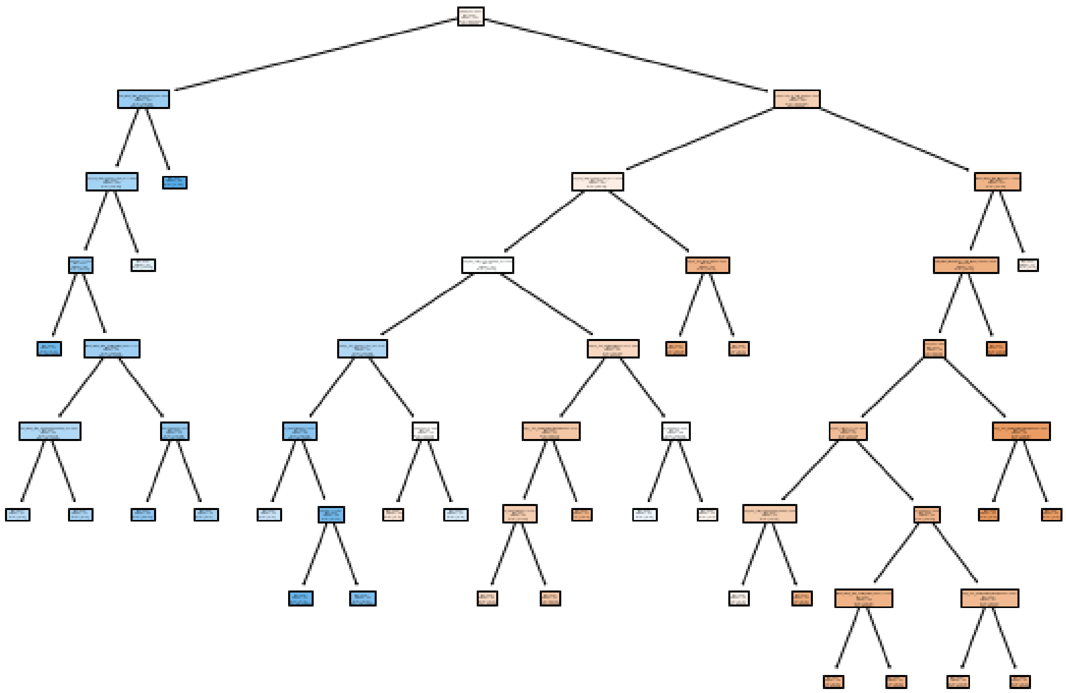
[14]:
```
for i in range (nbTree) :
    parameters= treesParmeters[i]
    clf = tree.DecisionTreeClassifier(
        splitter=parameters['splitter'],
        max_depth =parameters['max_depth'],
        min_samples_leaf =parameters['min_samples_leaf']
    )
```

```
    X_train, X_test, y_train, y_test = train_test_split(train_examples,␣
↪train_labels, test_size=0.2, random_state=42)

    clf = clf.fit(X_train, y_train)
    scores = cross_val_score(clf, X_test, y_test, cv=2)
    print("%0.2f accuracy with a standard deviation of %0.2f" % (scores.mean(),␣
↪scores.std()))
    plt.figure(figsize=(10,7))
    tree.plot_tree(clf,
                       feature_names= (features),
                       class_names= ("recidiviste", "non recidiviste"),
                       filled=True)
    plt.show()
```

```
0.66 accuracy with a standard deviation of 0.02
```

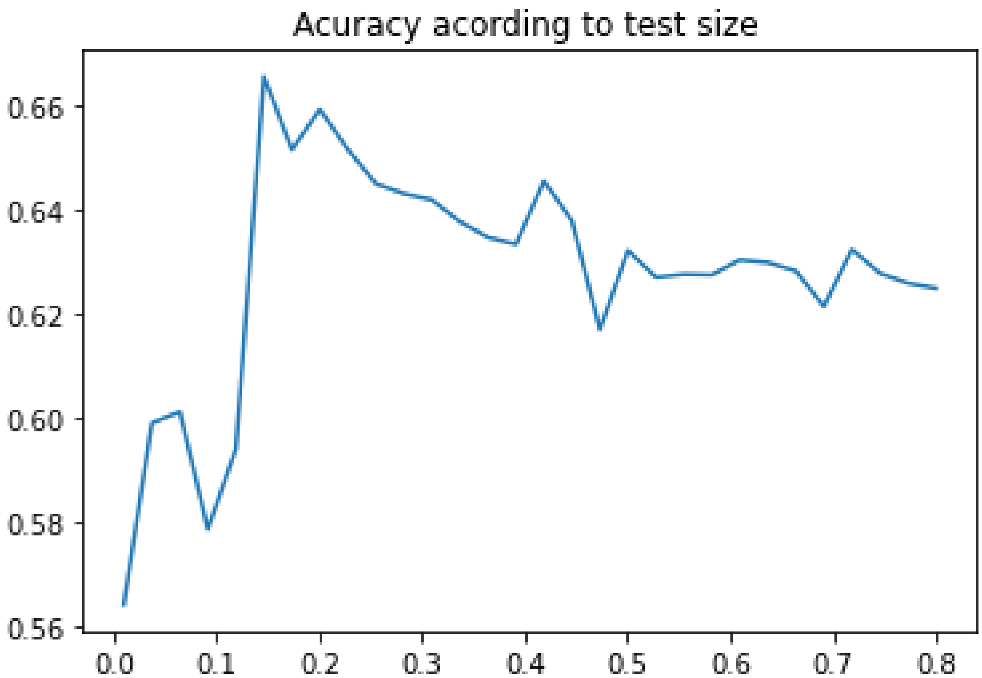



```
0.64 accuracy with a standard deviation of 0.01
```



Propose an experimental study that shows the transition phase from underfitting to overfitting

[15]:
```
parameters= treesParmeters[0]
acuracy =[]
test_sizes=np.linspace(0.01,0.8,30)
for test_size in test_sizes :
    clf = tree.DecisionTreeClassifier(
        splitter=parameters['splitter'],
        max_depth =parameters['max_depth'],
        min_samples_leaf =parameters['min_samples_leaf']
    )
    X_train, X_test, y_train, y_test = train_test_split(train_examples,␣
 ↪train_labels, test_size=test_size, random_state=42)

    clf = clf.fit(X_train, y_train)
    scores = cross_val_score(clf, X_test, y_test, cv=2)
    acuracy.append(scores.mean())
    #print(f"for a test size of {1/i} we have an accuracy of {scores.mean()}␣
 ↪with a standard deviation of {scores.std()}")
plt.title('Acuracy acording to test size ')
plt.plot(test_sizes,acuracy)
plt.show()
```



1.0.3 Remarks

- With small tests size, we have bad result because our graph is to close of our data
  - **this is overfitting**
- With high tests size, our results start to be be lower because the graph is constructed with too few data
  - **this is underfitting**

Construct the confusion matrix on a particular good configuration (after explaining your choice)

[16]:
```
parameters= treesParmeters[0]

clf = tree.DecisionTreeClassifier(
        splitter=parameters['splitter'],
        max_depth =parameters['max_depth'],
        min_samples_leaf =parameters['min_samples_leaf']
    )
X_train, X_test, y_train, y_test = train_test_split(train_examples,␣
 ↪train_labels, test_size=test_size, random_state=42)

clf = clf.fit(X_train, y_train)
#confusion_matrix(y_train, y_test)
```

Provide an evaluation of the fairness of the model based on the False Positive Rate

[ ]:
```

```