Overfitting (Printing accuracy at different steps)

In [8]:
```
# evaluate decision tree performance on train and test sets with different tree depths
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
from matplotlib import pyplot
```

In [9]:
```
# define dataset
X, y = make_classification(n_samples=10000, n_features=20, n_informative=5, n_redundant=15, random_state=1)
# summarize the dataset
print(X.shape, y.shape)
```

```
(10000, 20) (10000,)
```

In [10]:
```
# split into train test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1)
# summarize the shape of the train and test sets
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(9000, 20) (1000, 20) (9000,) (1000,)
```

In [11]:
```

train_scores, test_scores = list(), list()

# define the tree depths to evaluate
values = [i for i in range(1, 50)]
```

In [12]:

```python
# evaluate a decision tree for each depth
for i in values:
    # configure the model
    model = DecisionTreeClassifier(max_depth=i)
    # fit model on the training dataset
    model.fit(X_train, y_train)
    # evaluate on the train dataset
    train_yhat = model.predict(X_train)
    train_acc = accuracy_score(y_train, train_yhat)
    train_scores.append(train_acc)
    # evaluate on the test dataset
    test_yhat = model.predict(X_test)
    test_acc = accuracy_score(y_test, test_yhat)
    test_scores.append(test_acc)
    # summarize progress
    print('>%d, train: %.3f, test: %.3f' % (i, train_acc, test_acc))
```

```
>1, train: 0.765, test: 0.778
>2, train: 0.812, test: 0.806
>3, train: 0.883, test: 0.901
>4, train: 0.902, test: 0.913
>5, train: 0.914, test: 0.921
>6, train: 0.929, test: 0.931
>7, train: 0.937, test: 0.930
>8, train: 0.947, test: 0.931
>9, train: 0.956, test: 0.936
>10, train: 0.964, test: 0.941
>11, train: 0.968, test: 0.940
>12, train: 0.974, test: 0.933
>13, train: 0.980, test: 0.932
>14, train: 0.985, test: 0.922
>15, train: 0.988, test: 0.919
>16, train: 0.993, test: 0.924
>17, train: 0.995, test: 0.915
>18, train: 0.996, test: 0.917
>19, train: 0.997, test: 0.920
>20, train: 0.997, test: 0.914
>21, train: 0.998, test: 0.917
>22, train: 0.998, test: 0.915
```

```
>23, train: 0.998, test: 0.910
>24, train: 0.998, test: 0.917
>25, train: 0.999, test: 0.913
>26, train: 0.999, test: 0.912
>27, train: 0.999, test: 0.912
>28, train: 0.999, test: 0.914
>29, train: 1.000, test: 0.911
>30, train: 1.000, test: 0.915
>31, train: 1.000, test: 0.910
>32, train: 1.000, test: 0.917
>33, train: 1.000, test: 0.908
>34, train: 1.000, test: 0.916
>35, train: 1.000, test: 0.917
>36, train: 1.000, test: 0.914
>37, train: 1.000, test: 0.914
>38, train: 1.000, test: 0.913
>39, train: 1.000, test: 0.915
>40, train: 1.000, test: 0.908
>41, train: 1.000, test: 0.911
>42, train: 1.000, test: 0.912
>43, train: 1.000, test: 0.911
>44, train: 1.000, test: 0.909
>45, train: 1.000, test: 0.908
>46, train: 1.000, test: 0.912
>47, train: 1.000, test: 0.915
>48, train: 1.000, test: 0.911
>49, train: 1.000, test: 0.908
```

Cross-validation

In [13]:
```
#TASK 4

import numpy as np
from sklearn.model_selection import train_test_split
from sklearn import datasets
from sklearn import svm

X, y = datasets.load_wine(return_X_y=True)
X.shape, y.shape
```
Out[13]:
```
((178, 13), (178,))
```

Basic method to compute score

In [14]:
```
#TASK 4

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=0)

X_train.shape, y_train.shape

X_test.shape, y_test.shape


clf = svm.SVC(kernel='linear', C=1).fit(X_train, y_train)
clf.score(X_test, y_test)
```
Out[14]:
```
0.9814814814814815
```

Estimate the accuracy by splitting the data, computing the score 5 consecutive times (with different splits each time)

In [15]:
```
#TASK 4

from sklearn.model_selection import cross_val_score
clf = svm.SVC(kernel='linear', C=1, random_state=42)
scores = cross_val_score(clf, X, y, cv=5)
scores
```

Out[15]:
```
array([0.88888889, 0.94444444, 0.97222222, 1.        , 1.        ])
```

In [16]:
```
#TASK 4

print("%0.2f accuracy with a standard deviation of %0.2f" % (scores.mean(), scores.std()))
```

```
0.96 accuracy with a standard deviation of 0.04
```

Using the different scoring parameter

In [17]:
```
#TASK 4

from sklearn import metrics

scores = cross_val_score(
    clf, X, y, cv=5, scoring='f1_macro')
scores
```

Out[17]:
```
array([0.88763285, 0.94515263, 0.97401299, 1.        , 1.        ])
```

Specified multiple metrics of predefined scorer names

In [18]:
```python
#TASK 4

from sklearn.model_selection import cross_validate
from sklearn.metrics import recall_score

scoring = ['precision_macro', 'recall_macro']
clf = svm.SVC(kernel='linear', C=1, random_state=0)
scores = cross_validate(clf, X, y, scoring=scoring)
sorted(scores.keys())

scores['test_recall_macro']
```

Out[18]:
```
array([0.9047619 , 0.95238095, 0.97222222, 1.        , 1.        ])
```

Calculate cross validation score by passing a cross validation iterator

In [19]:
```python
#TASK 4

from sklearn.model_selection import ShuffleSplit
n_samples = X.shape[0]
cv = ShuffleSplit(n_splits=5, test_size=0.3, random_state=0)
cross_val_score(clf, X, y, cv=cv)
```

Out[19]:
```
array([0.98148148, 0.92592593, 0.94444444, 0.98148148, 0.94444444])
```

Use an iterable yielding (train, test) splits as arrays of indices

In [20]:

```
#TASK 4

def custom_cv_2folds(X):
    n = X.shape[0]
    i = 1
    while i <= 2:
        idx = np.arange(n * (i - 1) / 2, n * i / 2, dtype=int)
        yield idx, idx
        i += 1

custom_cv = custom_cv_2folds(X)
cross_val_score(clf, X, y, cv=custom_cv)
```

Out[20]:

```
array([1., 1.])
```

Different type of Cross validation iterators

K-fold

In [21]:

```
# TASK 4

import numpy as np
from sklearn.model_selection import KFold

X = ["a", "b", "c", "d"]
kf = KFold(n_splits=4)
for train, test in kf.split(X):
    print("%s %s" % (train, test))
```

```
[1 2 3] [0]
[0 2 3] [1]
[0 1 3] [2]
[0 1 2] [3]
```

Repeated K-Fold

In [22]:

```
import numpy as np
from sklearn.model_selection import RepeatedKFold
X = np.array([[1, 2], [3, 4], [1, 2], [3, 4]])
random_state = 12883823
rkf = RepeatedKFold(n_splits=2, n_repeats=2, random_state=random_state)
for train, test in rkf.split(X):
    print("%s %s" % (train, test))
```

```
[2 3] [0 1]
[0 1] [2 3]
[0 2] [1 3]
[1 3] [0 2]
```

Leave One Out (LOO)

In [23]:

```
from sklearn.model_selection import LeaveOneOut

X = [1, 2, 3, 4]
loo = LeaveOneOut()
for train, test in loo.split(X):
    print("%s %s" % (train, test))
```

```
[1 2 3] [0]
[0 2 3] [1]
[0 1 3] [2]
[0 1 2] [3]
```

Validation curve

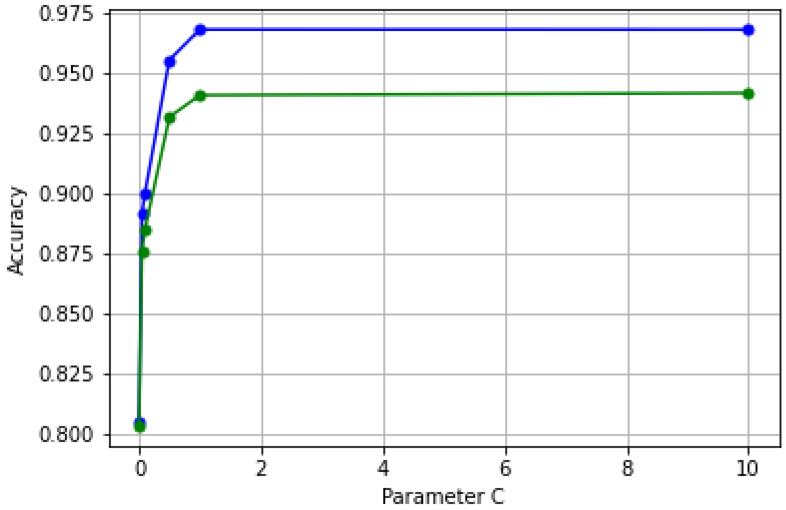
In [ ]:

```
######   MY
```

In [24]:

```
# TASK 4
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.model_selection import validation_curve
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import LogisticRegression
#
# IRIS Dataset is loaded
#
iris = datasets.load_iris()
df = pd.DataFrame(iris.data)
df.columns = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width']
df['species'] = iris.target
#
# Create training and test split
#
X_train, X_test, y_train, y_test = train_test_split(df.iloc[:, :-1], df.iloc[:, -1], test_size=0.3, random_state=1,
stratify=df.iloc[:, -1])
#
# Create the pipeline having steps for standardization and estimator as LogisticRegression
#
pipeline = make_pipeline(StandardScaler(), LogisticRegression(solver='lbfgs', penalty='l2', max_iter=10000, random_st
#
# Get Training and test scores using validation curve method
# Pay attention to the parameter values range set as param_range
#
param_range = [0.001, 0.05, 0.1, 0.5, 1.0, 10.0]
train_scores, test_scores = validation_curve(estimator=pipeline,
                                             X=X_train, y=y_train,
                                             cv=10,
param_name='logisticregression__C', param_range=param_range)
#
# Find the mean of training and test scores out of 10-fod StratifiedKFold cross validation run as part fo execution c
#
train_mean = np.mean(train_scores, axis=1)
test_mean = np.mean(test_scores, axis=1)
```

```python
#
# Plot the model scores (accuracy) against the paramater range
#
plt.plot(param_range, train_mean,
         marker='o', markersize=5,
         color='blue', label='Training Accuracy')
plt.plot(param_range, test_mean,
         marker='o', markersize=5,
         color='green', label='Validation Accuracy')
plt.xlabel('Parameter C')
plt.ylabel('Accuracy')
plt.grid()
plt.show()
```



ROC

In [25]:

```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
import matplotlib.pyplot as plt
```

In [26]:

```python
#import dataset from CSV file on Github
url = "https://raw.githubusercontent.com/Statology/Python-Guides/main/default.csv"
data = pd.read_csv(url)

#define the predictor variables and the response variable
X = data[['student', 'balance', 'income']]
y = data['default']

#split the dataset into training (70%) and testing (30%) sets
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=0)

#instantiate the model
log_regression = LogisticRegression()

#fit the model using the training data
log_regression.fit(X_train,y_train)
```

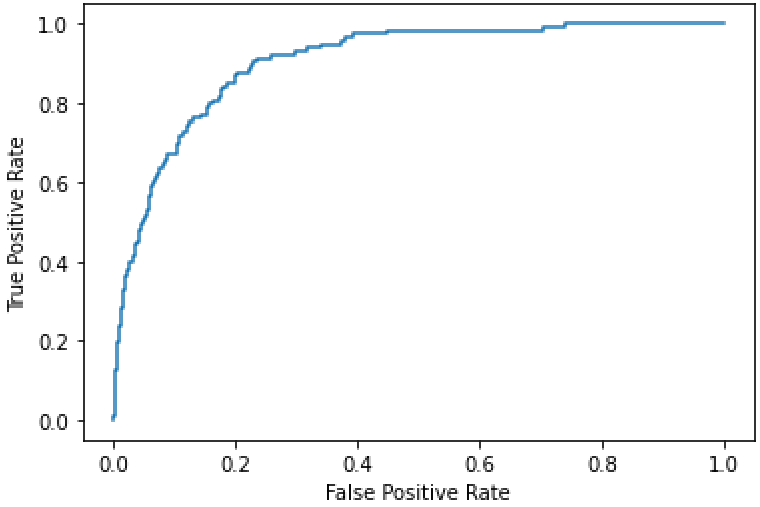
Out[26]:

```
LogisticRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

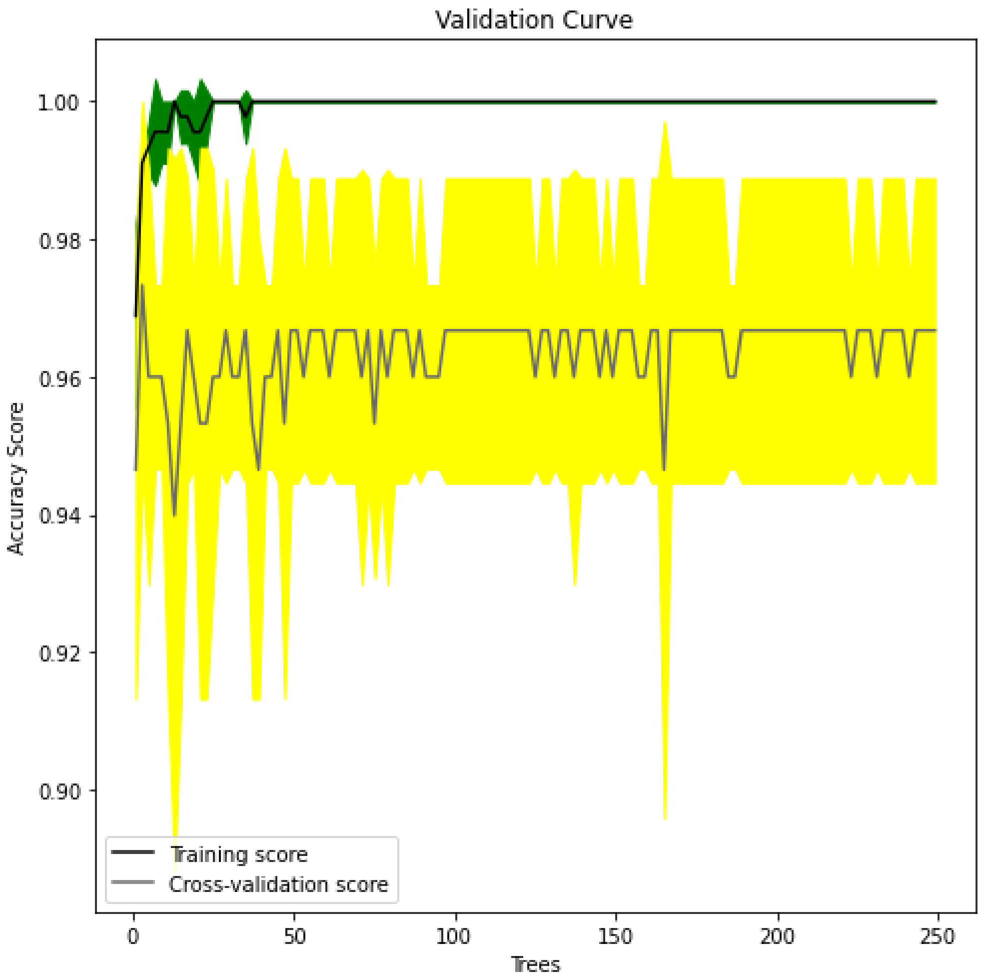
In [27]:

```
#split the dataset into training (70%) and testing (30%) sets
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=0)

#instantiate the model
log_regression = LogisticRegression()

#fit the model using the training data
log_regression.fit(X_train,y_train)

#define metrics
y_pred_proba = log_regression.predict_proba(X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)

#create ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



In [28]:

```
#TASK 4

from sklearn.ensemble import RandomForestClassifier
digits = datasets.load_iris()

X, y = digits.data, digits.target

param_range = np.arange(1, 250, 2)

train_scores, test_scores = validation_curve(RandomForestClassifier(),X, y, param_name="n_estimators", param_range=pa

train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)

test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

plt.subplots(1, figsize=(7,7))
plt.plot(param_range, train_mean, label="Training score", color="black")
plt.plot(param_range, test_mean, label="Cross-validation score", color="dimgrey")
plt.fill_between(param_range, train_mean - train_std, train_mean + train_std, color="green")
plt.fill_between(param_range, test_mean - test_std, test_mean + test_std, color="yellow")
plt.title("Validation Curve")
plt.xlabel("Trees")
plt.ylabel("Accuracy Score")
plt.tight_layout()
plt.legend(loc="best")
plt.show()
```


Validation Curve
Accuracy Score
Trees
1.00
0.98
0.96
0.94
0.92
0.90
0
50
100
150
200
250
Training score
Cross-validation score

In [ ]: