## **Exploring the Breast-Cancer Dataset**

We will use Recursive Feature Elimination (RFE): Tree Based and Gradient Boosting Estimators

We will employ RFE using:

- (1) the Tree based and
- (2) the Gradient Boosting

estimators.

\* Note: we will like to compare these results to 'SelectFromModel' method. So we will start with the later.

```
In [1]:
```

```
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [2]:
```

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.feature_selection import SelectFromModel, RFE
from sklearn.metrics import accuracy_score
```

```
In [3]:
```

```
from sklearn.datasets import load_breast_cancer
```

## We Import our Data

```
In [4]:
```

```
cancer = load_breast_cancer()
cancer.keys()
Out[4]:
dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names', 'filename'])
In [5]:
cancer.target_names
Out[5]:
array(['malignant', 'benign'], dtype='<U9')</pre>
In [6]:
```

```
X = pd.DataFrame(cancer.data, columns=cancer.feature_names)
```

```
In [7]:
```

```
y = cancer.target
```

```
X.head()
Out[8]:
                                                                                                                                               mean
                                                                                                                                                                                        mean
        mean
                       mean
                                          mean
                                                        mean
                                                                                mean
                                                                                                          mean
                                                                                                                             mean
                                                                                                                                                                   mean
                                                                                                                                                                                                           worst
                                                                                                                                                                                                                          worst
                                                                                                                                                                                                                                              wors
                                                                                                                                          concave
                                                                                                                                                                                      fractal
       radius
                    texture perimeter
                                                          area smoothness compactness concavity
                                                                                                                                                                                                          radius texture
                                                                                                                                                           symmetry
                                                                                                                                                                                                                                       perimete
                                                                                                                                              points
                                                                                                                                                                               dimension
        17.99
                        10.38
                                         122.80 1001.0
                                                                             0.11840
                                                                                                       0.27760
                                                                                                                            0.3001
                                                                                                                                           0.14710
                                                                                                                                                                 0.2419
                                                                                                                                                                                    0.07871 ...
                                                                                                                                                                                                            25.38
                                                                                                                                                                                                                           17.33
                                                                                                                                                                                                                                             184.60
                                                                                                                                                                                    0.05667 ...
        20.57
                        17.77
                                         132.90 1326.0
                                                                             0.08474
                                                                                                       0.07864
                                                                                                                            0.0869
                                                                                                                                            0.07017
                                                                                                                                                                 0.1812
                                                                                                                                                                                                            24.99
                                                                                                                                                                                                                           23.41
                                                                                                                                                                                                                                             158.80
         19.69
                        21.25
                                         130.00 1203.0
                                                                             0.10960
                                                                                                       0.15990
                                                                                                                            0.1974
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                                                                                                                                                                 0.2069
                                                                                                                                                                                    0.05999
                                                                                                                                                                                                            23.57
                                                                                                                                                                                                                           25.53
                                                                                                                                                                                                                                             152.50
                        20.38
                                          77.58
                                                        386.1
                                                                             0.14250
                                                                                                       0.28390
                                                                                                                            0.2414
                                                                                                                                           0.10520
                                                                                                                                                                 0.2597
                                                                                                                                                                                    0.09744 ...
                                                                                                                                                                                                                           26.50
                                                                                                                                                                                                                                              98.87
        11.42
                                                                                                                                                                                                            14.91
                                                                                                                                                                 0.1809
        20.29
                        14.34
                                         135.10 1297.0
                                                                             0.10030
                                                                                                       0.13280
                                                                                                                            0.1980
                                                                                                                                           0.10430
                                                                                                                                                                                    0.05883 ...
                                                                                                                                                                                                            22.54
                                                                                                                                                                                                                           16.67
                                                                                                                                                                                                                                             152.20
5 rows × 30 columns
                                                                                                                                                                                                                                                  Þ
In [9]:
X.shape, y.shape
Out[9]:
((569, 30), (569,))
In [10]:
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0, test_size=0.2)
In [11]:
X_train.shape, X_test.shape
Out[11]:
((455, 30), (114, 30))
Feature Selection by Feature Importance: Using SelectFromModel
We will use SelectFromModel with RandomForestClassifier
In [12]:
select = SelectFromModel(RandomForestClassifier(n_estimators=100, random_state=0, n_jobs=-1))
select.fit(X_train, y_train)
Out[12]:
SelectFromModel(estimator=RandomForestClassifier(n_jobs=-1, random_state=0))
In [13]:
select.get_support()
Out[13]:
array([ True, False, True, True, False, False, True, False, False
                 False, False, True, False, True, False, False, False,
                   True, False, False])
In [14]:
selected_features = X_train.columns[select.get_support()]
selected\_features
Out[14]:
Index(['mean radius', 'mean perimeter', 'mean area', 'mean concavity',
                   'mean concave points', 'area error', 'worst radius', 'worst perimeter',
                  'worst area', 'worst concave points'],
               dtype='object')
```

In [8]:

```
In [15]:
len(selected_features)
Out[15]:
10
In [16]:
X_train_select = select.transform(X_train)
X_test_select = select.transform(X_test)
In [17]:
X_train_select.shape, X_test_select.shape
Out[17]:
((455, 10), (114, 10))
In [18]:
def run_model(X_train, X_test, y_train, y_test):
    rf = RandomForestClassifier(n_estimators=100, random_state=0)
    rf.fit(X_train, y_train)
    y_pred = rf.predict(X_test)
    print('Accuracy score:', accuracy_score(y_test, y_pred))
In [19]:
print('---Raw Data (30 features)---')
run_model(X_train, X_test, y_train, y_test)
---Raw Data (30 features)---
Accuracy score: 0.9649122807017544
In [20]:
print('---Using Feature Importance (9 features)---')
run_model(X_train_select, X_test_select, y_train, y_test)
---Using Feature Importance (9 features)---
Accuracy score: 0.9473684210526315
We got a score of 94.74% using SelectFromModel with Random Forest Classifier.
Recursive Feature Elimination (RFE): Tree Based Estimator
In [21]:
for k in range(1, 31):
    sel = RFE(RandomForestClassifier(n_estimators=100, random_state=0, n_jobs=-1), n_features_to_select=k)
    sel.fit(X_train, y_train)
    X_train_sel = sel.transform(X_train)
    X_test_sel = sel.transform(X_test)
    print('Selected feature:', k)
    run_model(X_train_sel, X_test_sel, y_train, y_test)
    print()
Selected feature: 1
Accuracy score: 0.8947368421052632
Selected feature: 2
Accuracy score: 0.9298245614035088
Selected feature: 3
Accuracy score: 0.9473684210526315
Selected feature: 4
Accuracy score: 0.9649122807017544
Selected feature: 5
Accuracy score: 0.9649122807017544
Selected feature: 6
Accuracy score: 0.956140350877193
Selected feature: 7
Accuracy score: 0.956140350877193
```

Selected feature: 8

Accuracy score: 0.9649122807017544

Selected feature: 9

Accuracy score: 0.9736842105263158

Selected feature: 10

Accuracy score: 0.9736842105263158

Selected feature: 11

Accuracy score: 0.9649122807017544

Selected feature: 12

Accuracy score: 0.9736842105263158

Selected feature: 13

Accuracy score: 0.9649122807017544

Selected feature: 14

Accuracy score: 0.9736842105263158

Selected feature: 15

Accuracy score: 0.9736842105263158

Selected feature: 16

Accuracy score: 0.9736842105263158

Selected feature: 17

Accuracy score: 0.9824561403508771

Selected feature: 18

Accuracy score: 0.9649122807017544

Selected feature: 19

Accuracy score: 0.9649122807017544

Selected feature: 20

Accuracy score: 0.9736842105263158

Selected feature: 21

Accuracy score: 0.9736842105263158

Selected feature: 22

Accuracy score: 0.9736842105263158

Selected feature: 23

Accuracy score: 0.9649122807017544

Selected feature: 24

Accuracy score: 0.9824561403508771

Selected feature: 25

Accuracy score: 0.956140350877193

Selected feature: 26

Accuracy score: 0.956140350877193

Selected feature: 27

Accuracy score: 0.9649122807017544

Selected feature: 28

Accuracy score: 0.9649122807017544

Selected feature: 29

Accuracy score: 0.9649122807017544

Selected feature: 30

Accuracy score: 0.9649122807017544

## In [25]:

```
sel = RFE(RandomForestClassifier(n_estimators=100, random_state=0, n_jobs=-1), n_features_to_select=17)
sel.fit(X_train, y_train)
X_train_sel = sel.transform(X_train)
X_test_sel = sel.transform(X_test)
print('Selected feature:', 17)
run_model(X_train_sel, X_test_sel, y_train, y_test)
```

Selected feature: 17

Accuracy score: 0.9824561403508771

```
In [26]:
features = X_train.columns[sel.get_support()]
features
Out[26]:
Index(['mean radius', 'mean texture', 'mean perimeter', 'mean area',
       'mean concavity', 'mean concave points', 'radius error', 'area error',
       'worst radius', 'worst texture', 'worst perimeter', 'worst area',
       'worst smoothness', 'worst compactness', 'worst concavity',
       'worst concave points', 'worst symmetry'],
      dtype='object')
In [27]:
len(features)
Out[27]:
17
Recursive Feature Elimination: Gradient Boost Estimator
In [24]:
for k in range(1, 31):
    rfe = RFE(GradientBoostingClassifier(n_estimators=100, random_state=0), n_features_to_select=k)
    rfe.fit(X_train, y_train)
    X_train_rfe = rfe.transform(X_train)
    X_test_rfe = rfe.transform(X_test)
    print('Selected feature:', k)
    run_model(X_train_rfe, X_test_rfe, y_train, y_test)
    print()
Selected feature: 1
Accuracy score: 0.8771929824561403
Selected feature: 2
Accuracy score: 0.9035087719298246
Selected feature: 3
Accuracy score: 0.9649122807017544
Selected feature: 4
Accuracy score: 0.9736842105263158
Selected feature: 5
Accuracy score: 0.9649122807017544
Selected feature: 6
Accuracy score: 0.9912280701754386
Selected feature: 7
Accuracy score: 0.9736842105263158
Selected feature: 8
Accuracy score: 0.9649122807017544
Selected feature: 9
Accuracy score: 0.9736842105263158
Selected feature: 10
Accuracy score: 0.956140350877193
Selected feature: 11
Accuracy score: 0.956140350877193
Selected feature: 12
Accuracy score: 0.9736842105263158
```

Selected feature: 13

Selected feature: 14

Selected feature: 15

Selected feature: 16

Accuracy score: 0.956140350877193

Accuracy score: 0.956140350877193

Accuracy score: 0.9649122807017544

Accuracy score: 0.956140350877193

```
Accuracy score: 0.9649122807017544
Selected feature: 18
Accuracy score: 0.9473684210526315
Selected feature: 19
Accuracy score: 0.9649122807017544
Selected feature: 20
Accuracy score: 0.9473684210526315
Selected feature: 21
Accuracy score: 0.9649122807017544
Selected feature: 22
Accuracy score: 0.9649122807017544
Selected feature: 23
Accuracy score: 0.9649122807017544
Selected feature: 24
Accuracy score: 0.9649122807017544
Selected feature: 25
Accuracy score: 0.9736842105263158
Selected feature: 26
Accuracy score: 0.9736842105263158
Selected feature: 27
Accuracy score: 0.9649122807017544
Selected feature: 28
Accuracy score: 0.9649122807017544
Selected feature: 29
Accuracy score: 0.9649122807017544
Selected feature: 30
Accuracy score: 0.9649122807017544
In [28]:
rfe = RFE(GradientBoostingClassifier(n_estimators=100, random_state=0), n_features_to_select=6)
rfe.fit(X_train, y_train)
X_train_rfe = rfe.transform(X_train)
X_test_rfe = rfe.transform(X_test)
print('Selected feature:', 6)
run_model(X_train_rfe, X_test_rfe, y_train, y_test)
Selected feature: 6
Accuracy score: 0.9912280701754386
In [30]:
```

```
features = X_train.columns[rfe.get_support()]
features
```

## Out[30]:

Selected feature: 17

We got a score of 99.13% using RFE with Gradient Boosting Classifier.