DecisionTrees

November 28, 2025

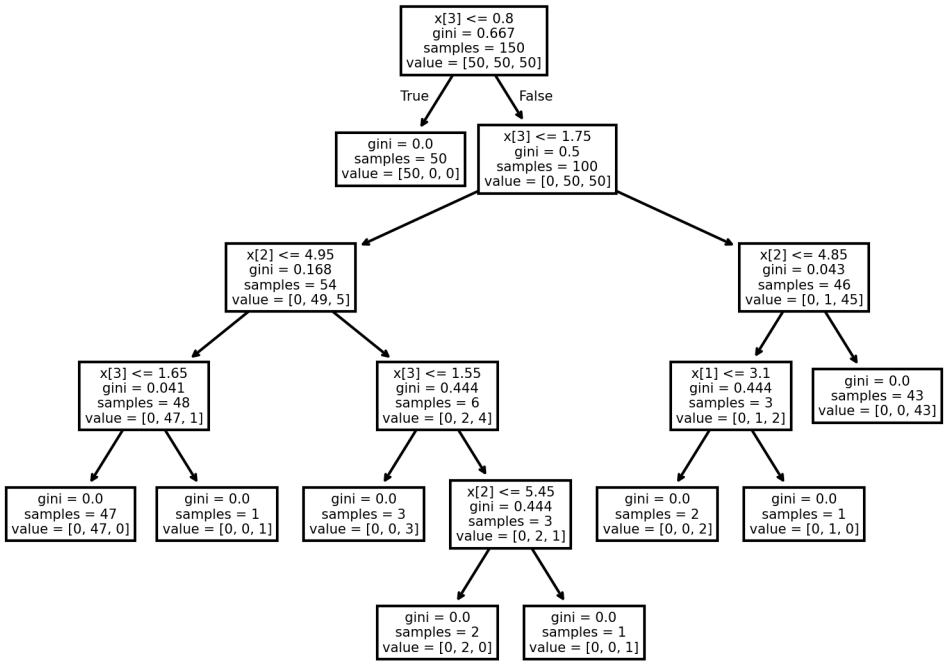
[15]:
```
import matplotlib.pyplot as plt
```

[8]:
```
from sklearn.datasets import load_iris
from sklearn import tree
from sklearn.tree import export_text
iris = load_iris()
X, y = iris.data, iris.target
clf = tree.DecisionTreeClassifier()
clf = clf.fit(X, y)
```

[18]:
```
plt.figure(dpi=300)
tree.plot_tree(clf)
```

[18]:
```
[Text(0.5, 0.9166666666666666, 'x[3] <= 0.8\ngini = 0.667\nsamples = 150\nvalue
= [50, 50, 50]'),
 Text(0.4230769230769231, 0.75, 'gini = 0.0\nsamples = 50\nvalue = [50, 0, 0]'),
 Text(0.46153846153846156, 0.8333333333333333, 'True  '),
 Text(0.5769230769230769, 0.75, 'x[3] <= 1.75\ngini = 0.5\nsamples = 100\nvalue
= [0, 50, 50]'),
 Text(0.5384615384615384, 0.8333333333333333, '  False'),
 Text(0.3076923076923077, 0.5833333333333334, 'x[2] <= 4.95\ngini =
0.168\nsamples = 54\nvalue = [0, 49, 5]'),
 Text(0.15384615384615385, 0.4166666666666667, 'x[3] <= 1.65\ngini =
0.041\nsamples = 48\nvalue = [0, 47, 1]'),
 Text(0.07692307692307693, 0.25, 'gini = 0.0\nsamples = 47\nvalue = [0, 47,
0]'),
 Text(0.23076923076923078, 0.25, 'gini = 0.0\nsamples = 1\nvalue = [0, 0, 1]'),
 Text(0.46153846153846156, 0.4166666666666667, 'x[3] <= 1.55\ngini =
0.444\nsamples = 6\nvalue = [0, 2, 4]'),
 Text(0.38461538461538464, 0.25, 'gini = 0.0\nsamples = 3\nvalue = [0, 0, 3]'),
 Text(0.5384615384615384, 0.25, 'x[2] <= 5.45\ngini = 0.444\nsamples = 3\nvalue
= [0, 2, 1]'),
 Text(0.46153846153846156, 0.08333333333333333, 'gini = 0.0\nsamples = 2\nvalue
= [0, 2, 0]'),
 Text(0.6153846153846154, 0.08333333333333333, 'gini = 0.0\nsamples = 1\nvalue =
[0, 0, 1]'),
 Text(0.8461538461538461, 0.5833333333333334, 'x[2] <= 4.85\ngini =
0.043\nsamples = 46\nvalue = [0, 1, 45]'),
```

```
 Text(0.7692307692307693, 0.4166666666666667, 'x[1] <= 3.1\ngini =
0.444\nsamples = 3\nvalue = [0, 1, 2]'),
 Text(0.6923076923076923, 0.25, 'gini = 0.0\nsamples = 2\nvalue = [0, 0, 2]'),
 Text(0.8461538461538461, 0.25, 'gini = 0.0\nsamples = 1\nvalue = [0, 1, 0]'),
 Text(0.9230769230769231, 0.4166666666666667, 'gini = 0.0\nsamples = 43\nvalue =
[0, 0, 43]')]
```



Each value array indicates how many of each kind fall under a particular split/leaf. We can see that during the first split itself, the DTree is able to separate out all the 50 flowers of the first type. The only further confusion is between types two and three. This is because the first group is linearly separable from the other two.

[10]:
```
iris.feature_names
```

[10]:
```
['sepal length (cm)',
 'sepal width (cm)',
 'petal length (cm)',
 'petal width (cm)']
```

[11]:
```
iris.target_names
```

[11]:
```
array(['setosa', 'versicolor', 'virginica'], dtype='<U10')
```

[13]:
```
tree_text = export_text(clf, feature_names=iris.feature_names) #Decision-Rule
print(tree_text)
```

```
|--- petal width (cm) <= 0.80
|   |--- class: 0
|--- petal width (cm) >  0.80
|   |--- petal width (cm) <= 1.75
|   |   |--- petal length (cm) <= 4.95
|   |   |   |--- petal width (cm) <= 1.65
|   |   |   |   |--- class: 1
|   |   |   |--- petal width (cm) >  1.65
|   |   |   |   |--- class: 2
|   |   |--- petal length (cm) >  4.95
|   |   |   |--- petal width (cm) <= 1.55
|   |   |   |   |--- class: 2
|   |   |   |--- petal width (cm) >  1.55
|   |   |   |   |--- petal length (cm) <= 5.45
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- petal length (cm) >  5.45
|   |   |   |   |   |--- class: 2
|   |--- petal width (cm) >  1.75
|   |   |--- petal length (cm) <= 4.85
|   |   |   |--- sepal width (cm) <= 3.10
|   |   |   |   |--- class: 2
|   |   |   |--- sepal width (cm) >  3.10
|   |   |   |   |--- class: 1
|   |   |--- petal length (cm) >  4.85
|   |   |   |--- class: 2
```