Decision tree

December 18, 2022

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

[2]:
```
from sklearn.datasets import load_iris
```

[3]:
```
iris=load_iris()
iris
```

[3]:
```
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 'frame': None,
 'target_names': array(['setosa', 'versicolor', 'virginica'], dtype='<U10'),
 'DESCR': '.. _iris_dataset:\n\nIris plants
dataset\n--------------------\n\n**Data Set Characteristics:**\n\n    :Number of
Instances: 150 (50 in each of three classes)\n    :Number of Attributes: 4
numeric, predictive attributes and the class\n    :Attribute Information:\n
- sepal length in cm\n        - sepal width in cm\n        - petal length in
cm\n        - petal width in cm\n        - class:\n                - Iris-
Setosa\n                - Iris-Versicolour\n                - Iris-Virginica\n
\n    :Summary Statistics:\n\n    ============== ==== ==== ======= =====
====================\n                    Min  Max   Mean    SD   Class
Correlation\n    ============== ==== ==== ======= ===== ====================\n
```

```
sepal length:   4.3  7.9   5.84   0.83    0.7826\n    sepal width:    2.0  4.4
3.05   0.43   -0.4194\n    petal length:   1.0  6.9   3.76   1.76    0.9490
(high!)\n    petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)\n
============== ==== ==== ======= ===== ====================\n\n    :Missing
Attribute Values: None\n    :Class Distribution: 33.3% for each of 3 classes.\n
:Creator: R.A. Fisher\n    :Donor: Michael Marshall
(MARSHALL%PLU@io.arc.nasa.gov)\n    :Date: July, 1988\n\nThe famous Iris
database, first used by Sir R.A. Fisher. The dataset is taken\nfrom Fisher\'s
paper. Note that it\'s the same as in R, but not as in the UCI\nMachine Learning
Repository, which has two wrong data points.\n\nThis is perhaps the best known
database to be found in the\npattern recognition literature.  Fisher\'s paper is
a classic in the field and\nis referenced frequently to this day.  (See Duda &
Hart, for example.)  The\ndata set contains 3 classes of 50 instances each,
where each class refers to a\ntype of iris plant.  One class is linearly
separable from the other 2; the\nlatter are NOT linearly separable from each
other.\n\n.. topic:: References\n\n   - Fisher, R.A. "The use of multiple
measurements in taxonomic problems"\n     Annual Eugenics, 7, Part II, 179-188
(1936); also in "Contributions to\n     Mathematical Statistics" (John Wiley,
NY, 1950).\n   - Duda, R.O., & Hart, P.E. (1973) Pattern Classification and
Scene Analysis.\n     (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See
page 218.\n   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New
System\n     Structure and Classification Rule for Recognition in Partially
Exposed\n     Environments".  IEEE Transactions on Pattern Analysis and
Machine\n     Intelligence, Vol. PAMI-2, No. 1, 67-71.\n   - Gates, G.W. (1972)
"The Reduced Nearest Neighbor Rule".  IEEE Transactions\n     on Information
Theory, May 1972, 431-433.\n   - See also: 1988 MLC Proceedings, 54-64.
Cheeseman et al"s AUTOCLASS II\n     conceptual clustering system finds 3
classes in the data.\n   - Many, many more …',
 'feature_names': ['sepal length (cm)',
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 'data_module': 'sklearn.datasets.data'}
```

[4]:
```
iris.data
```

[4]:
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       [4.9, 3.1, 1.5, 0.1],
```

```
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[5.9, 3. , 5.1, 1.8]])
```

[5]:
```
iris.target
```

[5]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
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```

[6]:
```
import seaborn as sns
```

[7]:
```
df=sns.load_dataset('iris')
```

[8]:
```
df.head()
```

[8]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

[9]:
```
X=df.iloc[:,:-1]
y=iris.target
```

[10]:
```
X,y
```

[10]:
```
(     sepal_length  sepal_width  petal_length  petal_width
 0             5.1          3.5           1.4          0.2
 1             4.9          3.0           1.4          0.2
 2             4.7          3.2           1.3          0.2
 3             4.6          3.1           1.5          0.2
 4             5.0          3.6           1.4          0.2
 ..            …            …             …            …
 145           6.7          3.0           5.2          2.3
 146           6.3          2.5           5.0          1.9
 147           6.5          3.0           5.2          2.0
 148           6.2          3.4           5.4          2.3
 149           5.9          3.0           5.1          1.8

 [150 rows x 4 columns],
 array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
        1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
        1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
```

```
2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2]))
```

[11]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
     X, y, test_size=0.33, random_state=42)
```

[12]:
```
X_train
```

[12]:

	sepal_length	sepal_width	petal_length	petal_width
96	5.7	2.9	4.2	1.3
105	7.6	3.0	6.6	2.1
66	5.6	3.0	4.5	1.5
0	5.1	3.5	1.4	0.2
122	7.7	2.8	6.7	2.0
..	…	…	…	…
71	6.1	2.8	4.0	1.3
106	4.9	2.5	4.5	1.7
14	5.8	4.0	1.2	0.2
92	5.8	2.6	4.0	1.2
102	7.1	3.0	5.9	2.1

[100 rows x 4 columns]

[13]:
```
from sklearn.tree import DecisionTreeClassifier
```

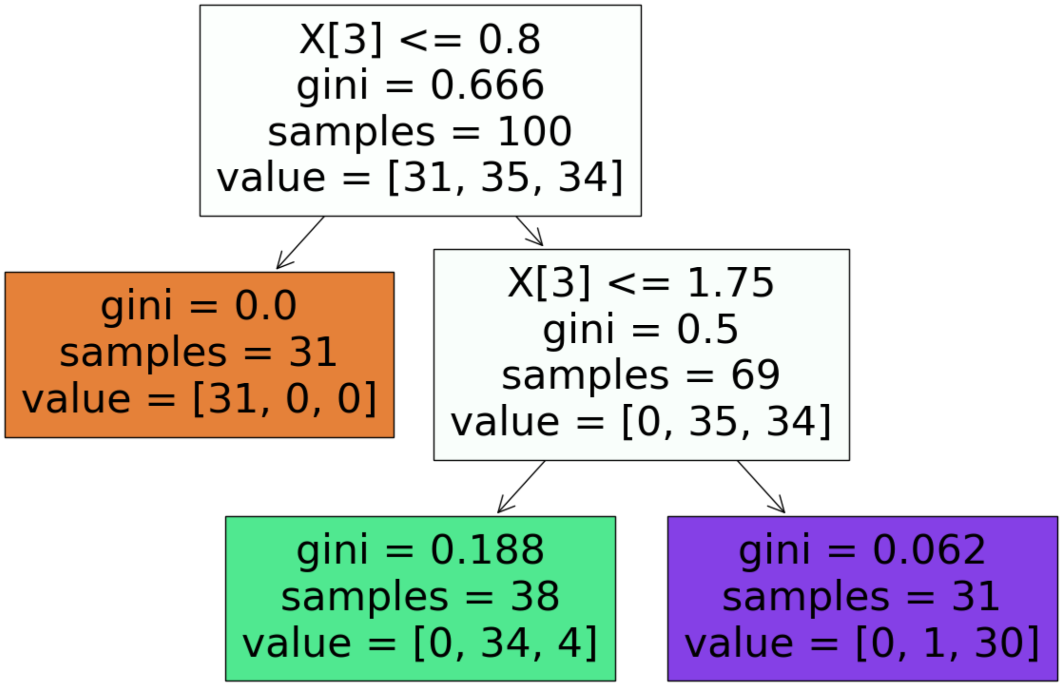
[14]:
```
treemodel=DecisionTreeClassifier(max_depth=2)
```

[15]:
```
treemodel.fit(X_train,y_train)
```

[15]:
```
DecisionTreeClassifier(max_depth=2)
```

[16]:
```
from sklearn import tree
plt.figure(figsize=(15,10))
tree.plot_tree(treemodel,filled=True)
```

[16]:
```
[Text(0.4, 0.8333333333333334, 'X[3] <= 0.8\ngini = 0.666\nsamples = 100\nvalue
= [31, 35, 34]'),
 Text(0.2, 0.5, 'gini = 0.0\nsamples = 31\nvalue = [31, 0, 0]'),
 Text(0.6, 0.5, 'X[3] <= 1.75\ngini = 0.5\nsamples = 69\nvalue = [0, 35, 34]'),
 Text(0.4, 0.16666666666666666, 'gini = 0.188\nsamples = 38\nvalue = [0, 34,
4]'),
 Text(0.8, 0.16666666666666666, 'gini = 0.062\nsamples = 31\nvalue = [0, 1,
30]')]
```



[17]:
```
y_pred=treemodel.predict(X_test)
```

[18]:
```
y_pred
```

[18]:
```
array([1, 0, 2, 1, 1, 0, 1, 2, 1, 1, 2, 0, 0, 0, 0, 1, 2, 1, 1, 2, 0, 2,
       0, 2, 2, 2, 2, 2, 0, 0, 0, 0, 1, 0, 0, 2, 1, 0, 0, 0, 2, 1, 1, 0,
       0, 1, 1, 2, 1, 2])
```

[19]:
```
from sklearn.metrics import accuracy_score,classification_report
```

[20]:
```
score=accuracy_score(y_pred,y_test)
print(score)
```

```
0.98
```

[21]:
```
print(classification_report(y_pred,y_test))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       1.00      0.94      0.97        16
           2       0.94      1.00      0.97        15

    accuracy                           0.98        50
```

```
   macro avg       0.98      0.98      0.98        50
weighted avg       0.98      0.98      0.98        50
```

```
[ ]:
```