

1、导入数据

In [1]:

```
import os
import pandas as pd
```

In [2]:

```
dir_ds = os.path.join(os.path.curdir, 'lenses.txt')
df_data = pd.read_csv(dir_ds, sep='\t', header=None, names=['age', 'spectacle', 'astigmatic', 'tear', 'class'])
df_data
```

Out[2]:

| | age | spectacle | astigmatic | tear | class |
|----|------------|-----------|------------|---------|-----------|
| 0 | young | myope | no | reduced | no lenses |
| 1 | young | myope | no | normal | soft |
| 2 | young | myope | yes | reduced | no lenses |
| 3 | young | myope | yes | normal | hard |
| 4 | young | hyper | no | reduced | no lenses |
| 5 | young | hyper | no | normal | soft |
| 6 | young | hyper | yes | reduced | no lenses |
| 7 | young | hyper | yes | normal | hard |
| 8 | pre | myope | no | reduced | no lenses |
| 9 | pre | myope | no | normal | soft |
| 10 | pre | myope | yes | reduced | no lenses |
| 11 | pre | myope | yes | normal | hard |
| 12 | pre | hyper | no | reduced | no lenses |
| 13 | pre | hyper | no | normal | soft |
| 14 | pre | hyper | yes | reduced | no lenses |
| 15 | pre | hyper | yes | normal | no lenses |
| 16 | presbyopic | myope | no | reduced | no lenses |
| 17 | presbyopic | myope | no | normal | no lenses |
| 18 | presbyopic | myope | yes | reduced | no lenses |
| 19 | presbyopic | myope | yes | normal | hard |
| 20 | presbyopic | hyper | no | reduced | no lenses |
| 21 | presbyopic | hyper | no | normal | soft |
| 22 | presbyopic | hyper | yes | reduced | no lenses |
| 23 | presbyopic | hyper | yes | normal | no lenses |

2、决策树算法

In [3]:

```
import numpy as np
from sklearn.preprocessing import LabelEncoder
```

In [4]:

```
ds = LabelEncoder()
# 定义数据的标签
ds.fit(['no lenses', 'hard', 'soft', 'young', 'pre', 'presbyopic', 'myope', 'hyper', 'no', 'yes', 'reduced', 'normal'])
arr_data = np.array([ds.transform(r) for i, r in df_data.iterrows()])
arr_data
```

Out[4]:

```
array([[11, 2, 3, 8, 4],
       [11, 2, 3, 5, 9],
       [11, 2, 10, 8, 4],
       [11, 2, 10, 5, 0],
       [11, 1, 3, 8, 4],
       [11, 1, 3, 5, 9],
       [11, 1, 10, 8, 4],
       [11, 1, 10, 5, 0],
       [ 6, 2, 3, 8, 4],
       [ 6, 2, 3, 5, 9],
       [ 6, 2, 10, 8, 4],
       [ 6, 2, 10, 5, 0],
       [ 6, 1, 3, 8, 4],
       [ 6, 1, 3, 5, 9],
       [ 6, 1, 10, 8, 4],
       [ 6, 1, 10, 5, 4],
       [ 7, 2, 3, 8, 4],
       [ 7, 2, 3, 5, 4],
       [ 7, 2, 10, 8, 4],
       [ 7, 2, 10, 5, 0],
       [ 7, 1, 3, 8, 4],
       [ 7, 1, 3, 5, 9],
       [ 7, 1, 10, 8, 4],
       [ 7, 1, 10, 5, 4]])
```

In [5]:

```
from sklearn.model_selection import train_test_split
```

In [6]:

```
training_set, testing_set = train_test_split(arr_data, test_size = 0.4) # 分割训练集
training_set
```

Out[6]:

```
array([[ 6,  2,  3,  8,  4],
       [ 7,  2,  3,  8,  4],
       [11,  1, 10,  5,  0],
       [ 6,  2, 10,  5,  0],
       [ 6,  2,  3,  5,  9],
       [11,  1,  3,  5,  9],
       [ 6,  1, 10,  5,  4],
       [ 6,  1,  3,  8,  4],
       [ 7,  2, 10,  8,  4],
       [11,  1, 10,  8,  4],
       [ 6,  1, 10,  8,  4],
       [ 6,  2, 10,  8,  4],
       [11,  2,  3,  8,  4],
       [ 7,  1, 10,  5,  4]])
```

In [7]:

```
testing_set
```

Out[7]:

```
array([[11,  2, 10,  5,  0],
       [ 7,  2,  3,  5,  4],
       [11,  2, 10,  8,  4],
       [ 7,  1, 10,  8,  4],
       [ 7,  2, 10,  5,  0],
       [ 7,  1,  3,  5,  9],
       [ 7,  1,  3,  8,  4],
       [11,  1,  3,  8,  4],
       [ 6,  1,  3,  5,  9],
       [11,  2,  3,  5,  9]])
```

In [8]:

```
X_train = training_set[:,0:4]
Y_train = training_set[:,4]
X_test = testing_set[:,0:4]
Y_test = testing_set[:,4]
```

In [9]:

```
from sklearn import tree
```

In [10]:

```
model_dt = tree.DecisionTreeClassifier(criterion='entropy')
model_dt = model_dt.fit(X_train, Y_train)
```

In [11]:

```
y_pre = model_dt.predict(X_test)
y_pre
```

Out[11]:

```
array([0, 9, 4, 4, 0, 9, 4, 4, 9, 9])
```

In [12]:

```
Y_test
```

Out[12]:

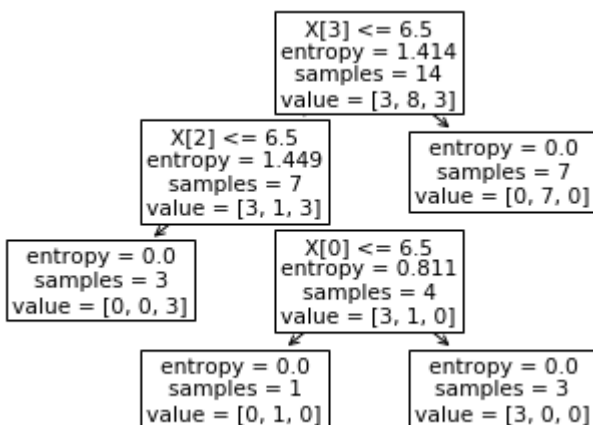
```
array([0, 4, 4, 4, 0, 9, 4, 4, 9, 9])
```

In [44]:

```
tree.plot_tree(model_dt) # 使用sklearn的决策树算法
```

Out[44]:

```
[Text(200.88000000000002, 190.26, 'X[3] <= 6.5\nentropy = 1.414\nsamples = 14\nvalue = [3, 8, 3]'),
 Text(133.92000000000002, 135.9, 'X[2] <= 6.5\nentropy = 1.449\nsamples = 7\nvalue = [3, 1, 3]'),
 Text(66.96000000000001, 81.53999999999999, 'entropy = 0.0\nsamples = 3\nvalue = [0, 0, 3]'),
 Text(200.88000000000002, 81.53999999999999, 'X[0] <= 6.5\nentropy = 0.811\nsamples = 4\nvalue = [3, 1, 0]'),
 Text(133.92000000000002, 27.180000000000007, 'entropy = 0.0\nsamples = 1\nvalue = [0, 1, 0]'),
 Text(267.84000000000003, 27.180000000000007, 'entropy = 0.0\nsamples = 3\nvalue = [3, 0, 0]'),
 Text(267.84000000000003, 135.9, 'entropy = 0.0\nsamples = 7\nvalue = [0, 7, 0]')]
```



3、对实验数据进行回归和预测

In [45]:

```
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score
```

In [46]:

```
confusion_matrix(Y_test, y_pre, labels=[0, 4, 9]) # 混淆矩阵
```

Out[46]:

```
array([[0, 1, 0],
       [1, 5, 1],
       [0, 0, 2]], dtype=int64)
```

In [47]:

```
accuracy_score(Y_test, y_pre) # 分类正确的百分比
```

Out[47]:

0.7

In [48]:

```
precision_score(Y_test, y_pre, labels=[0, 4, 9], average='micro') # 分类的计算精度
```

Out[48]:

0.7

In [49]:

```
recall_score(Y_test, y_pre, labels=[0, 4, 9], average='micro') # 召回率: 提取出的正确信息条数/样本中的信息条数
```

Out[49]:

0.7

In [50]:

```
f1_score(Y_test, y_pre, labels=[0, 4, 9], average='micro') # f1值: 精确率和召回率的调和平均数
```

Out[50]:

0.7

In []: