决策树实验报告

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决策树算法原理：

1.首先将所有的特征看成一个个节点，创建出根节点；

2.然后遍历所有的特征，在每一次到某个特征时遍历当前特征的所有分割方式，找到最好的分割点，讲数据划分为不同的子节点，计算划分后子节点的信息熵

3.在遍历的所以特征中，比较寻找最优的特征以及最优特征的最优划分方式，选择信息增益最高的特征作为节点进行分割操作，产生子树

4．重复 2-3 步，直到子节点中只有一种类型或为空，或者当前节点中样本数小于某个值，同时迭代次数达到指定值

核心代码：

创建决策树

```
#创建树
def createTree(dataset,labels):
    classList=[example[-1] for example in dataset]
    if classList.count(classList[0]) == len(classList):
        return classList[0]
    if len(dataset[0]) == 1:
        return majority(classList)
    best_feature = chooseBestSplit(dataset)
    label = labels[best_feature]
    tree = {label:{}}
    del(labels[best_feature])
    feature_values = [example[best_feature] for example in dataset]
    unique_vals = set(feature_values)
    for value in unique_vals:
        sub_labels=labels[:]
        tree[label][value]=createTree(splitDataset(dataset,best_feature,value),sub_labels)
    return tree
```

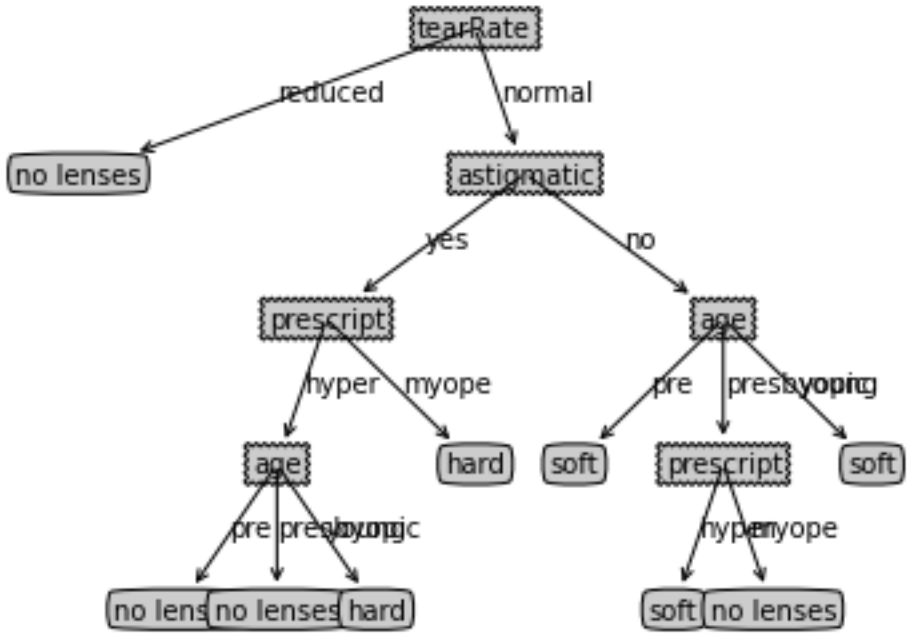
计算香浓熵

```
#计算香浓熵
def calShannon(dataset):
    size = len(dataset)
    label={}
    for feature in dataset:
        current_label=feature[-1]
        if current_label not in label.keys():
            label[current_label]=0

        label[current_label] +=1

    shannon=0.0
    for key in label:
        probability=float(label[key])/size
        shannon -= probability * log(probability,2)
    return shannon
```

选择最优的划分

```
#选择最好的数据集划分方式
def chooseBestSplit(dataset):
    num_features = len(dataset[0])-1
    base = calShannon(dataset)
    best_info_gain = 0.0
    best_feature = -1
    for i in range(num_features):
        feature_list = [example[i] for example in dataset]
        unique_vals = set(feature_list)
        new = 0.0
        for value in unique_vals:
            sub_dataset = splitDataset(dataset,i,value)
            probability = len(sub_dataset)/float(len(dataset))
            new += probability * calShannon(sub_dataset)
        info_gain = base-new
        if info_gain > best_info_gain:
            best_info_gain = info_gain
            best_feature = i

    return best_feature
```

实验结果: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