

编程实践:基于决策树和 C4.5 算法进行二分类





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问题背景



● 二分类

outlook	temperature	humidity	windy	result
sunny	hot	high	false	N
sunny	hot	high	true	N
overcast	hot	high	false	Y
rain	mild	high	false	Y
rain	cool	normal	false	Y
rain	cool	normal	true	N
overcast	cool	normal	true	Y

问题背景



● 训练集

outlook	temperature	humidity	windy	result
sunny	hot	high	false	N
sunny	hot	high	true	N
overcast	hot	high	false	Y
rain	mild	high	false	Y
rain	cool	normal	false	Y
rain	cool	normal	true	N
overcast	cool	normal	true	Y

问题背景



● 测试集

outlook	temperature	humidity	windy
sunny	mild	high	false
sunny	cool	normal	false
rain	mild	normal	false
sunny	mild	normal	true
overcast	mild	high	true
overcast	hot	normal	false
rain	mild	high	true



```
# -*- coding: utf-8 -*-
 2 from math import log
  import operator
   import treePlotter
   def calcShannonEnt(dataSet):
 6
       输入:数据集
 8
       输出:数据集的香农熵
       描述: 计算给定数据集的香农熵; 熵越大, 数据集的混乱程度越大
10
11
12
       numEntries = len(dataSet)
       labelCounts = \{\}
13
       for featVec in dataSet:
14
           currentLabel = featVec[-1]
15
           if currentLabel not in labelCounts.keys():
16
               labelCounts[currentLabel] = 0
17
           labelCounts[currentLabel] += 1
18
       shannonEnt = 0.0
19
       for key in labelCounts:
20
           prob = float(labelCounts[key])/numEntries
21
           shannonEnt -= prob * log(prob, 2)
22
       return shannonEnt
23
```



```
def splitDataSet(dataSet, axis, value):
25
26
       输入:数据集,选择维度,选择值
27
       输出:划分数据集
28
       描述:按照给定特征划分数据集;去除选择维度中等于选择值的项
29
30
       retDataSet = []
31
       for featVec in dataSet:
32
          if featVec[axis] == value:
33
              reduceFeatVec = featVec[:axis]
34
              reduceFeatVec.extend(featVec[axis+1:])
35
              retDataSet.append(reduceFeatVec)
36
       return retDataSet
37
```



```
def chooseBestFeatureToSplit(dataSet):
40
41
       输入:数据集
42
       输出:最好的划分维度
       描述: 选择最好的数据集划分维度
43
44
45
       numFeatures = len(dataSet[0]) - 1
       baseEntropy = calcShannonEnt(dataSet)
46
47
       bestInfoGainRatio = 0.0
       bestFeature = -1
48
       for i in range(numFeatures):
49
           featList = [example[i] for example in dataSet]
50
           uniqueVals = set(featList)
51
           newEntropy = 0.0
52
           splitInfo = 0.0
53
           for value in uniqueVals:
54
               subDataSet = splitDataSet(dataSet, i, value)
55
               prob = len(subDataSet)/float(len(dataSet))
56
57
               newEntropy += prob * calcShannonEnt(subDataSet)
               splitInfo += -prob * log(prob, 2)
58
           infoGain = baseEntropy - newEntropy
59
           if (splitInfo == 0): # fix the overflow bug
60
               continue
61
           infoGainRatio = infoGain / splitInfo
62
           if (infoGainRatio > bestInfoGainRatio):
63
               bestInfoGainRatio = infoGainRatio
64
               bestFeature = i
65
       return bestFeature
66
```



```
68
   def majorityCnt(classList):
69
70
       输入:分类类别列表
       输出: 子节点的分类
71
72
            采用多数判决的方法决定该子节点的分类
73
74
75
       classCount = {}
       for vote in classList:
76
           if vote not in classCount.keys():
77
78
               classCount[vote] = 0
           classCount[vote] += 1
79
       sortedClassCount = sorted(classCount.iteritems(), key=operator.itemgetter(1), reversed=True)
80
       return sortedClassCount[0][0]
81
```



```
def createTree(dataSet, labels):
 84
        输入:数据集,特征标签
85
        输出:决策树
86
        描述: 递归构建决策树, 利用上述的函数
 87
 88
        classList = [example[-1] for example in dataSet]
 89
        if classList.count(classList[0]) == len(classList):
 90
            # 类别完全相同, 停止划分
 91
            return classList[0]
92
        if len(dataSet[0]) == 1:
93
            # 遍历完所有特征时返回出现次数最多的
94
            return majorityCnt(classList)
 95
        bestFeat = chooseBestFeatureToSplit(dataSet)
 96
        bestFeatLabel = labels[bestFeat]
 97
        myTree = {bestFeatLabel:{}}
98
        del(labels[bestFeat])
99
100
        # 得到列表包括节点所有的属性值
101
        featValues = [example[bestFeat] for example in dataSet]
        uniqueVals = set(featValues)
102
        for value in uniqueVals:
103
104
            subLabels = labels[:]
105
           myTree[bestFeatLabel][value] = createTree(splitDataSet(dataSet, bestFeat, value), subLabels)
106
        return myTree
```



```
108
    def classify(inputTree, featLabels, testVec):
109
        输入:决策树,分类标签,测试数据
110
        输出:决策结果
111
112
        描述: 跑决策树
113
114
        firstStr = list(inputTree.keys())[0]
115
        secondDict = inputTree[firstStr]
        featIndex = featLabels.index(firstStr)
116
        for key in secondDict.keys():
117
            if testVec[featIndex] == key:
118
                if type(secondDict[key]). name == 'dict':
119
120
                    classLabel = classify(secondDict[key], featLabels, testVec)
                else:
121
122
                    classLabel = secondDict[key]
        return classLabel
123
```



```
def classifyAll(inputTree, featLabels, testDataSet):
125
126
        输入:决策树,分类标签,测试数据集
127
        输出:决策结果
128
        描述:跑决策树
129
130
131
        classLabelAll = []
132
        for testVec in testDataSet:
           classLabelAll.append(classify(inputTree, featLabels, testVec))
133
        return classLabelAll
134
```



```
def storeTree(inputTree, filename):
136
137
        输入:决策树,保存文件路径
138
        输出:
139
        描述:保存决策树到文件
140
141
        import pickle
142
        fw = open(filename, 'wb')
143
        pickle.dump(inputTree, fw)
144
        fw.close()
145
```



```
def grabTree(filename):
147
148
        输入:文件路径名
149
        输出:决策树
150
        描述:从文件读取决策树
151
152
        import pickle
153
        fr = open(filename, 'rb')
154
        return pickle.load(fr)
155
```



```
157
    def createDataSet():
158
         outlook-> 0: sunny | 1: overcast | 2: rain
159
        temperature-> 0: hot | 1: mild | 2: cool
160
161
         humidity-> 0: high | 1: normal
        windy-> 0: false | 1: true
162
163
         dataSet = [[0, 0, 0, 0, 'N'],
164
165
                    [0, 0, 0, 1, 'N'],
                    [1, 0, 0, 0, 'Y'],
166
                    [2, 1, 0, 0, 'Y'],
167
                    [2, 2, 1, 0, 'Y'],
168
169
                    [2, 2, 1, 1, 'N'],
                    [1, 2, 1, 1, 'Y']]
170
         labels = ['outlook', 'temperature', 'humidity', 'windy']
171
172
         return dataSet, labels
```

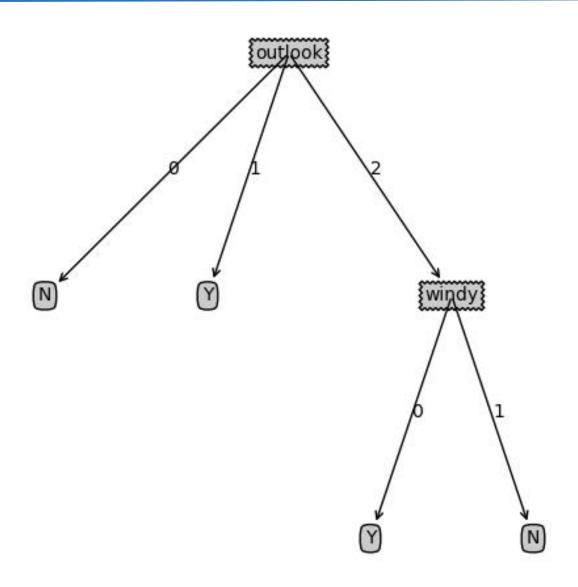


```
def createTestSet():
174
175
         outlook-> 0: sunny | 1: overcast | 2: rain
176
         temperature-> 0: hot | 1: mild | 2: cool
177
         humidity-> 0: high | 1: normal
178
         windy-> 0: false | 1: true
179
180
         testSet = [[0, 1, 0, 0],
181
                     [0, 2, 1, 0],
182
                    [2, 1, 1, 0],
183
184
                    [0, 1, 1, 1],
                    [1, 1, 0, 1],
185
                     [1, 0, 1, 0],
186
                     [2, 1, 0, 1]]
187
188
         return testSet
```



```
190
    def main():
191
        dataSet, labels = createDataSet()
192
        labels_tmp = labels[:] # 拷贝, createTree会改变labels
193
        desicionTree = createTree(dataSet, labels tmp)
194
        #storeTree(desicionTree, 'classifierStorage.txt')
195
        #desicionTree = grabTree('classifierStorage.txt')
196
        print('desicionTree:\n', desicionTree)
        treePlotter.createPlot(desicionTree)
197
        testSet = createTestSet()
198
199
        print('classifyResult:\n', classifyAll(desicionTree, labels, testSet))
200
    if __name__ == '__main__':
201
        main()
202
```

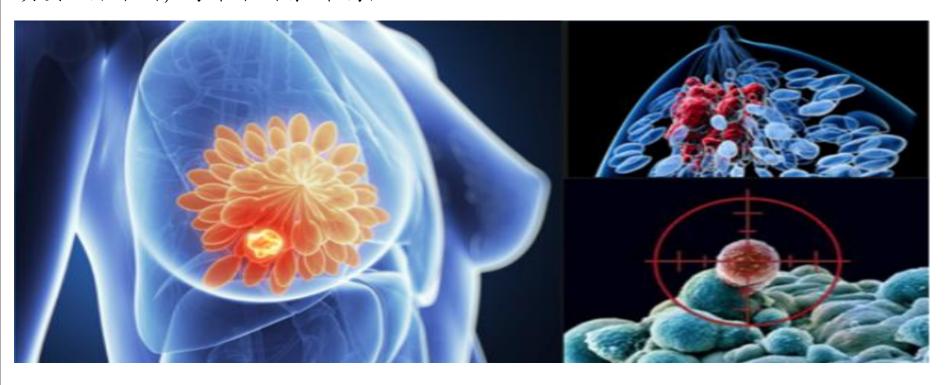




课后作业



这些年来很多人因为癌症逝世,其中不乏娱乐圈中的一线明星们,而乳腺癌也成了很多女星不幸离世的原因。这种病症已经引起了来自社会的关注,定期检查变得很有必要。Wisconsin医学院的william H.Wolberg博士提供乳腺癌数据样本。所欲数据来自真实临床案例,每个案例有9个属性。



数据来源: http://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/

课后作业



Attribute

Domain

-- ------

1. Sample code number id number

2. Clump Thickness 1 - 10

3. Uniformity of Cell Size 1 - 10

4. Uniformity of Cell Shape 1 - 10

5. Marginal Adhesion 1 - 10

6. Single Epithelial Cell Size 1 - 10

7. Bare Nuclei 1 - 10

8. Bland Chromatin 1 - 10

9. Normal Nucleoli 1 - 10

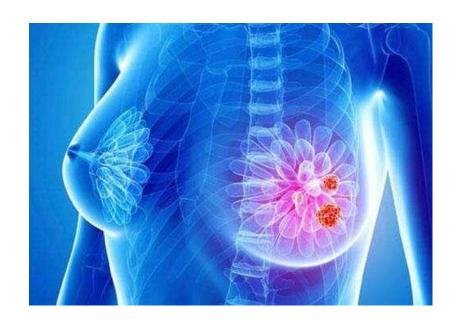
10. Mitoses 1 - 10

11. Class: (2 for benign, 4 for malignant)

Class distribution:

Benign: 458 (65.5%)

Malignant: 241 (34.5%)



课后作业



请你使用附件中提供的数据: Breastdata.txt

使用决策树和 C4.5 算法,选择 80% 的数据作为训练集,剩余 80% 的数据作为测试集,然后预测下面这位患者【5,7,6,10,8,4,6,5,4】(9个属性的检测结果,分别用1-10表示)是患良性还是恶性肿瘤。提示:重难点是原始数据的读取,切割,后面稍微调整。



数据来源: http://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/





Q&A







感谢各位聆听

请批评指正

