# 决策树算法实现实验报告

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#### 一、 数据预处理

首先将数据里,含有垃圾值的记录删除。

例如如下情况:

```
Asso midstand 200 months of months a post temper and a months of the foreign properties of the months of the product sample worked great. Honever, when I went to fill my prescription, even WITM insurance 19982 Alterlaytine and the months of the product sample worked great. Honever, when I went to fill my prescription, even WITM insurance 19982 Alterlaytine and the months of the product sample worked great. Honever, when I went to fill my prescription, even WITM insurance 19982 Alterlaytine and the product sample worked great. Honever, when I went to fill my prescription, even WITM insurance 19982 Alterlaytine and the product sample worked great. Honever, when I went to fill my prescription, even WITM insurance 19982 Alterlaytine and the product sample worked great. Honever, when I was not of the work of the product sample worked great. Honever, when I was not of the product sample worked great. Honever, when I was not of the product sample worked great. Honever, when I was not only subject to get injuried and insurance and the product of the product sample worked great. Honever, when I was not even to work the product of the product of the product is not been deeply and the product of th
```

删除明显与 rating 没有关系的列 recordID, review Comment 和 date

之后,为了使数据更好处理,对 drugName, condition, sideEffects 进行编码,

具体编码策略如下:对于每个不同的值,用数字代替

```
dict_drug = {}
  count = 0
  for i in sorted(set(drug_name)):
      dict_drug[i] = count
      count+=1
```

之后为上述三个属性和 usefulCount 分别计算训练集中它们与 rating 的皮尔逊相关系数. 结果如下:

```
C:\Users\dell\anaconda3\python.exe C:/Users/dell/Desktop/机器学习/homework03/test.py
drugname:(0.009750756805287624, 0.4169258341295182)
condition:(0.0445341297135339, 0.000207841408653436)
sideeffect:(0.01313751786735927, 0.2740687498421191)
usefulcount:(0.21809318186080934, 1.9774580652887071e-75)
Process finished with exit code 0
```

发现四者中只有 condition 和 usefulCount 的 p 值小于 0.05, 故舍弃其他两个

# 最终数据集如下:

■ condition ≎	■ usefulCount ≎	<b>I</b> ∄ rating ≎
108	22	5
101	17	4
401	3	5
417	35	5
54	4	5
217	13	2
54	1	3
246	32	5
280	21	4
54	3	1
183	17	1
407	7	3
417	57	1
351	19	5
205	44	1
257	14	5
368	26	5
3	1	2
53	24	3
401	9	5

## 二、 决策树算法

## 1、信息熵

一个节点信息熵, $p_k$ 是每个属性出现的概率。

$$\operatorname{Ent}_D = -\sum_{k=1}^K p_k * \log_2 p_k$$

每种特征中每个属性的信息熵 $Ent_{D_v}$ 

每个特征的信息熵

$$\sum_{1}^{V} \frac{D_{v}}{D} \operatorname{Ent}_{D_{v}}$$

信息增益. a 是属性

$$Gain_{(D,a)} = \operatorname{Ent}_{D} - \sum_{1}^{V} \frac{D_{v}}{D} \operatorname{Ent}_{D_{v}}$$

#### 算法过程

- 1. 将所有的特征看成一个一个的节点。创建根节点。
- 2. 遍历所有特征。遍历到其中某一个特征时,遍历当前特征的所有分割方式,找到最好的分割点,将数据划分为不同的子节点,计算划分后子节点的信息熵。
- 3. 在遍历的所有特征中,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,根据特征则对当前数据集进行分割操作,产生子树。
- 4. 对新的子节点继续执行 2 3 步, 直到下面的停止条件退出循环。 停止条件:
- 1. 当子节点中只有一种类型或为空的时候停止构建(会导致过拟合)
- 2. 当前节点种样本数小于某个值,同时迭代次数达到指定值,停止构建,此时使用该节点中出现最多的类别样本数据作为对应值(比较常用)

核心代码:

1、建树

```
class_list = [example[-1] for example in dataSet] #取出标签
if class_list.count(class_list[0]) == len(class_list):
   return majorCnt(class_list)
best_feat, best_part_value = chooseBestFeatureToSplit_c(dataSet, labelProperty)
#如果无法选出最优分类特征,返回次数最多的类别
if(labelProperty[best_feat] == 0):
   best_feat_label = labels[best_feat]
   myTree = {best_feat_label: {}}
   labelPropertyNew = copy.copy(labelProperty)
```

#### 2、计算信息熵并寻找最佳信息增益

def createTree(dataSet, labels, labelProperty):

```
def chooseBestFeatureToSplit_c(dataSet, labelProperty):
   feature_number = len(labelProperty)
   base_entropy = calcShannonEnt(dataSet)
   best_info_gain = 0.0
   best_feature = -1 #初始化最佳特征的索引值
   best_part_value = None
   for i in range(feature_number):
       features = [example[i] for example in dataSet]
       unique_feature = set(features)
       entropy = 0.0
       best_part_value_i = None
       if labelProperty[i] == 0: #处理离散化
           for value in unique_feature:
               subDataSet = splitDataSet(dataSet, i, value)
               prob = len(subDataSet) / float(len(dataSet))
               entropy += prob * calcShannonEnt(subDataSet)
```

```
else: #处理注意的特征

sorted_unique_feature = list(unique_feature)
sorted_unique_feature.sort()
# min_entropy = float("-inf")
min_entropy = 999999999

for j in range(len(sorted_unique_feature) - 1): #计算划分点
    part_value = (float(sorted_unique_feature[j]) + float(sorted_unique_feature[j + 1])) / 2
    dataSetLeft = splitDataSet_c(dataSet, i, part_value, 'L')
    dataSetRight = splitDataSet_c(dataSet, i, part_value, 'R')
    prob_left = len(dataSetLeft) / float(len(dataSet))
    prob_right = len(dataSetRight) / float(len(dataSet))
    entropy_temp = prob_left * calcShannonEnt(dataSetLeft) + prob_right * calcShannonEnt(dataSetRight)
    if entropy_temp < min_entropy:
        min_entropy = entropy_temp
        best_part_value_i = part_value
    entropy = min_entropy
info_gain = base_entropy - entropy
if info_gain > best_info_gain:
    best_info_gain = info_gain
    best_feature = i
    best_part_value = best_part_value_i

return best_feature, best_part_value
```

### 三、 实验结果

ount<18.5': {'yes': 5, 'no': 4}}}}}, 'no': 5}}}, 'no': ('yes': ('yes': ('yes': ('yes': ('yes': 1, 'no': 4)), 'no': ('condition<292.0': ('yes': 5, 'no': ('yes': 5, 'no': ('yes': 5, 'no': ('yes': 6, 'no': 6))})))))), 'no': ('usefulCount<116.0': ('yes': ('condition<317.5': ('yes': 1, 'no': 5)), 'no': 5})))), 'no': ('usefulCount<117.5': ('yes': 1, 'no': 5)), 'no': ('yes': 4, 'no': 5))))))))))), 'no': ('usefulCount<117.5': ('yes': 5, 'no': ('yes': 6'condition<231.5': ('yes': 4, 'no': 5))))))))))))), 'no': ('usefulCount<117.5': ('yes': 5, 'no': 4)), 'no': 5)), 'no': ('yes': 6'condition<231.5': ('yes': 6'yes': 6'yes': ('condition<231.5': ('yes': 6'yes': 6'y

Micro F1: 0.3844856661045531

Macro F1: 0.22777483939168724

测试集预测结果部分展示:

I condition ÷	■ usefulCount ÷	I⊞ rating ÷
54	1	5
84	θ	4
133	13	5
368	7	3
257	11	5
169	21	5
293	86	5
94	76	5
115	46	5
211	21	4
26	1	5
1	8	2
54	Θ	5
234	32	5
368	2	5
293	72	5
179	29	5
54	1	5
133	24	5
133	4	5
54	31	4
133	2	5
30	23	5
54	6	5
115	15	5
115	31	1
191	10	5
363	37	5
417	5	5
368	22	5
242	28	5
108	35	4
250	2	5
54	2	1
160	6	5
0	12	5
417	42	5